



Faculty of Economics and Business

**The Influence of Online Service Quality towards Customer Satisfaction
and Repurchase Intention in Chinese Fresh E-commerce**

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The Influence of Online Service Quality towards Customer Satisfaction and
Repurchase Intention in Chinese Fresh E-commerce

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DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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ABSTRACT

China's fresh e-commerce has expanded rapidly, yet service-quality volatility, rising complaints, and unstable repurchase behavior persist. The category's perishability, time sensitivity, cold-chain dependence, and high-frequency, low-ticket transactions make customer experience especially sensitive to fulfillment, logistics, customer service, and price perceptions. Against this backdrop, the study focuses on the mechanism linking service quality, satisfaction, and repurchase intention.

Existing research on fresh e-commerce provides incomplete empirical evidence on the service quality–satisfaction–repurchase mechanism. First, it relies heavily on cross-sectional questionnaires and lacks large-scale observations rooted in real purchasing and review contexts, limiting visibility into negative experiences and exception handling. Second, samples often come from a single platform or business model, overlooking heterogeneity across front-warehouse systems, store-warehouse integration, community group-buying, and comprehensive e-commerce, which constrains external validity. Third, prior work insufficiently distinguishes which service elements directly drive repurchase versus those that act primarily through satisfaction, and systematic mediation testing remains scarce. Therefore, there is a need to build and test an integrated model on multi-platform, real review data to clarify key paths and effect sizes linking service quality to satisfaction and repurchase.

This study tests the effects of online service-quality dimensions on customer satisfaction and repurchase intention and evaluates the mediating role of satisfaction. Specifically: (i) examine the effect of service quality on satisfaction; (ii) test the direct effect of service quality on repurchase intention; (iii) assess the effect of satisfaction on repurchase intention;

and (iv) evaluate the mediating role of satisfaction in the relationship between service quality and repurchase intention.

Using 56,765 user reviews from JD Fresh, Dingdong Maicai, Yonghui Delivery, and Taocaicai, the study applies BERTopic to extract service topics and elements. Subsequently, Baidu NLP's sentiment classifier assigns polarity (positive/neutral/negative) score to review texts mapped to each service-quality dimension, and the resulting scores are aggregated as measurement indicators. Direct and indirect effects are estimated via structural equation modeling (SEM), with mediation evaluated through bootstrap resampling.

Logistics service quality, customer service, and economic efficiency exhibit significant positive direct effects on repurchase intention. Fulfillment and ease of use significantly improve satisfaction but do not directly drive repurchase. Satisfaction both positively influences repurchase intention and plays a pivotal mediating role between service quality and repurchase.

Fresh e-commerce platforms should strengthen cold-chain operations, ensure on-time delivery, improve after-sales response, align pricing and membership benefits, and reduce errors in fulfillment and design. At the policy level, higher standards and review-based monitoring can promote healthier competition.

Keywords: fresh e-commerce, e-service quality, customer satisfaction, repurchase intention

Pengaruh Kualiti Perkhidmatan Dalam Talian terhadap Kepuasan Pelanggan dan Niat Pembelian Semula dalam E-Dagang Segar Cina

ABSTRAK

Sektor e-dagang barangan segar di China berkembang pesat, namun ketidakstabilan kualiti perkhidmatan, peningkatan aduan, dan tingkah laku pembelian semula yang tidak konsisten masih berterusan. Sifat mudah rosak, kepekaan masa, kebergantungan kepada rantaian sejuk, serta transaksi berfrekuensi tinggi bernilai kecil menjadikan pengalaman pelanggan sangat sensitif terhadap pemenuhan pesanan, logistik, perkhidmatan pelanggan, dan persepsi harga. Bertitik tolak daripada realiti ini, kajian memfokuskan mekanisme yang menghubungkan kualiti perkhidmatan, kepuasan, dan niat pembelian semula.

Bukti empirikal sedia ada mengenai mekanisme kualiti perkhidmatan–kepuasan–pembelian semula dalam konteks e-dagang barangan segar masih tidak mencukupi. Pertama, penyelidikan banyak bergantung pada soal selidik rentas-sekseyen dan kekurangan pemerhatian berskala besar yang berasaskan konteks pembelian dan ulasan sebenar, sekali gus mengehadkan kefahaman tentang pengalaman negatif serta pengendalian kejadian luar jangka. Kedua, sampel kerap datang daripada satu platform atau satu model perniagaan, mengabaikan kepelbagaian antara model operasi seperti gudang hadapan, integrasi kedai-gudang, pembelian berkumpulan komuniti, dan platform menyeluruh, yang seterusnya mengehadkan kesahan luaran. Ketiga, penyelidikan terdahulu kurang jelas membezakan unsur perkhidmatan yang memacu pembelian semula secara langsung berbanding unsur yang berfungsi terutamanya melalui kepuasan, dan pengujian perantaraan yang sistematik masih terhad. Justeru, perlu dibangunkan dan diuji satu model bersepadu menggunakan data ulasan sebenar merentas pelbagai platform untuk memperjelas laluan utama serta

magnitud kesannya yang menghubungkan kualiti perkhidmatan dengan kepuasan dan niat pembelian semula.

Kajian ini menguji kesan dimensi kualiti perkhidmatan dalam talian terhadap kepuasan pelanggan dan niat pembelian semula serta menilai peranan pengantara kepuasan. Secara khusus: (i) meneliti kesan kualiti perkhidmatan terhadap kepuasan; (ii) menguji kesan langsung kualiti perkhidmatan terhadap niat pembelian semula; (iii) menilai kesan kepuasan terhadap niat pembelian semula; dan (iv) menilai peranan pengantara kepuasan dalam hubungan antara kualiti perkhidmatan dan niat pembelian semula.

Menggunakan 56,765 ulasan pengguna daripada JD Fresh, Dingdong Maicai, Yonghui Delivery dan Taocaicai, kajian itu menggunakan BERTopic untuk mengekstrak topik dan elemen perkhidmatan. Selepas itu, pengelas sentimen Baidu NLP memberikan skor kekutuban (positif/neutral/negatif) untuk menyemak teks yang dipetakan pada setiap dimensi kualiti perkhidmatan, dan skor yang terhasil diagregatkan sebagai penunjuk ukuran. Kesan langsung dan tidak langsung dianggarkan melalui pemodelan persamaan struktur (SEM), dengan pengantaraan dinilai melalui pensampelan semula bootstrap.

Kualiti perkhidmatan logistik, perkhidmatan pelanggan, dan kecekapan ekonomi menunjukkan kesan positif langsung yang signifikan terhadap niat pembelian semula. Pemenuhan pesanan (fulfillment) dan kemudahan penggunaan meningkatkan kepuasan secara signifikan tetapi tidak secara langsung memacu pembelian semula. Kepuasan bukan sahaja mempengaruhi niat pembelian semula secara positif, malah berperanan sebagai pengantara penting antara kualiti perkhidmatan dan pembelian semula.

Platform e-dagang segar harus memperkuat operasi rantai sejuk, memastikan penghantaran tepat pada masanya, meningkatkan respons selepas jualan, menyelaraskan harga dan faedah keahlian, serta mengurangkan kesilapan dalam pemenuhan dan reka bentuk. Pada peringkat dasar, piawaian yang lebih tinggi dan pemantauan berasaskan ulasan dapat menggalakkan persaingan industri yang lebih sihat.

Kata kunci: *e-dagang barangan segar; kualiti perkhidmatan dalam talian; kepuasan pelanggan; niat pembelian semula*

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LIST OF ABBREVIATIONS

SQ	Service Quality
E-SQ	E-Service Quality
Fulfill	Fulfillment
EU	Ease of Use
CSE	Customer Service
LSQ	Logistics Service Quality
EE	Economic Efficiency
CS	Customer Satisfaction
RI	Repurchase Intention
SOR	Stimulus-Organism-Response
ECT	Expectation-Confirmation Theory
MEC	Means-Ends Chain
BERT	Bidirectional Encoder Representations from Transformers
TF	Term Frequency
DF	Document Frequency
IDF	Inverse Document Frequency
TF-IDF	Term Frequency-Inverse Document Frequency
c-TF-IDF	Class-based Term Frequency-Inverse Document Frequency
UMAP	Uniform Manifold Approximation and Projection
HDBSCAN	Hierarchical Density-Based Spatial Clustering of Applications with Noise
MMR	Maximal Marginal Relevance
SEM	Structural Equation Modeling

CHAPTER 1

INTRODUCTION

1.1 Introduction

In the digital age, technology has assumed a new and vital role in the business environment. The rapid advancement of internet-related information technology has significantly altered how people purchase products and services. When it comes to buying groceries, many people's first instinct is to pick and choose at bustling food markets. However, with the rise of online fresh e-commerce and related delivery services, people have been "liberated" from the traditional grocery shopping process. On newly emerging e-commerce platforms, customers have access to a diverse range of items, including fruits, vegetables, eggs, meats, and seafood. Amidst the COVID-19 pandemic, the security and convenience of "online ordering with fresh produce delivered to doorsteps" have led consumers to recognize the benefits offered by fresh retail platforms more deeply. According to Network Economy Society (2025), the transaction scale of China's fresh e-commerce industry reached 736.79 billion RMB in 2024. From 2014 to 2024, the market expanded each year without interruption, rising from 29 billion to 736.79 billion, which indicates sustained growth over the entire period. Meanwhile, the fresh e-commerce industry reached a user base of 577 million in 2024, a 12.47% increase from 2023, indicating a rising consumer acceptance of fresh e-commerce.

This chapter begins with an in-depth introduction to the background of the study, outlining the key characteristics and emerging trends of fresh e-commerce in China. Subsequently, a problem statement is formulated, emphasizing the lack of systematic analysis of post-purchase feedback in the context of online fresh produce retail and the

necessity for a more comprehensive understanding of service quality aspects. The objective of this research is to address these gaps by investigating the interrelationships between service quality, consumer satisfaction, and repurchase intentions. Research questions and objectives are delineated to guide the inquiry. The significance of this study lies in academic knowledge of service quality in fresh e-commerce and providing implications for enterprises, policymakers, and consumers.

1.2 Background of the Study

Fresh agricultural products, as a necessity in daily life, exhibit typical characteristics of high-frequency and rigid demand in consumers' purchasing behavior (Meng et al., 2022). According to the "2019 China Fresh Food Market Outlook Analysis Report" published by Nielsen, Chinese consumers made an average of three fresh food purchases per week in 2018. Among them, fruits and vegetables were frequently repurchased and had extremely high requirements for freshness, followed by fish and seafood products (Chen et al., 2021). China's macroeconomic environment remained supportive, with household income and consumption steadily improving and greater priority placed on food and grocery outlays. From 2016 to 2020, per capita food expenditure rose consistently; in 2020, it reached RMB 6,397, a 5.1 percent increase over 2019 (RMB 6,084). In 2020, per capita food spending accounted for 30.2 percent of total per capita consumption expenditure (Xiang & Cui, 2022).

In recent years, with the acceleration of the pace of life and the continuous evolution of consumption habits, the trend of consumers exploring new ways to obtain fresh, high-quality ingredients has become increasingly significant (Lin et al., 2021). This trend not only reflects consumers' higher requirements for food safety, health, and convenience, but also highlights the market's urgent need for innovative retail models and supply chain

optimization. Especially during the COVID-19 pandemic that broke out worldwide in 2020, this public health event has altered people's lifestyles, and the implementation of social distancing measures has had a profound impact on retail and food supply chains (Benhassen et al., 2020). During the pandemic, to avoid gatherings and reduce the risk of virus transmission associated with going out, consumers have had to seek safer and more convenient shopping methods. Against this backdrop, the e-commerce model has rapidly emerged as a crucial means of meeting the demand for fresh food, thanks to its advantages of contactless delivery, online shopping, flexibility, and convenience. In 2024, food consumption expenditure among China's urban residents totaled RMB 2.174 trillion, of which transactions conducted via fresh e-commerce accounted for 33.9 percent (Network Economy Society, 2025). It shows that Chinese consumers' behavior regarding the purchase of fresh food has significantly shifted towards online platforms (Gao et al., 2020).

As an integral component of the national digital economy, the fresh e-commerce functions as a strategic engine for rural revitalization and the dual circulation strategy. On the supply side, enterprises catalyze the digital transformation of agricultural circulation by investing in cold chain logistics, developing innovative warehousing, and building digital platforms, while strengthening digital infrastructure in rural areas (Du & Lu, 2023). They provide producers with direct market access, enhance product value through quality signaling and standardized packaging, and increase farm incomes. On the demand side, the sector meets rising consumer expectations for food safety, convenience, and quality, and advances the modernization of agricultural distribution and retail systems. In parallel, it creates employment along the entire supply chain: production, grading and packaging, warehousing, logistics and last-mile delivery, customer service, and information technology support. Consequently, fresh e-commerce enterprises are not only profitable business models

but also strategic drivers that upgrade consumption, improve the efficiency of agricultural and food supply systems, and contribute materially to rural revitalization and the development of the digital economy (Wang et al., 2023).

1.2.1 Development Status of Chinese Fresh E-commerce

Fresh agricultural commodities encompass primary produce that remains unprocessed or has undergone only basic handling such as washing, grading, and portioning. These items are prone to spoilage when stored at ambient temperatures and include a range of products like fruits, vegetables, meats, eggs, dairy, and seafood, among others. With the progression of the Internet, e-commerce has emerged as a novel avenue for selling fresh agricultural goods. Despite a later start in China, the fresh e-commerce sector has experienced swift growth. Since 2005, China's fresh produce e-commerce has undergone a series of transformations, broadly categorized into three stages: the initial exploration and launch phase, the period of accelerated expansion, and the era of transformation and enhancement, as outlined in Table 1.1.

Fresh commerce consumption is characterized by essential, day-to-day demand and high repurchase frequency, which has prompted substantial entry by platforms and entrepreneurs. From 2014 to 2024, the market expanded continuously, with the transaction scale rising from RMB 29.0 billion to RMB 736.79 billion (see Figure 1.1). Over this period, the growth rate exhibited an overall deceleration: the peak occurred in 2014 at 123.07 percent; after a temporary pandemic-era uptick in 2020 (42.54 percent), growth moderated to 14.67 percent by 2024.

The 52nd "Statistical Report on Internet Development in China," published by the China Internet Network Information Center (CNNIC) on August 28, 2023, indicates that the

total count of internet users in China now stands at 1.079 billion. The proportion of fresh e-commerce users as a percentage of total netizens and the overall proportion of online retail users among netizens are both relatively low. Data from the Economic Network reveals that in 2022, the market penetration of fresh e-commerce in China stood at 10.28%. When compared to China's current internet penetration rate of 76.4%, it's clear that the adoption of fresh e-commerce remains relatively low.

Table 1.1: Development Stages of China's Fresh e-commerce

Development Stage	Explore the Start-up Period (2005-2011)	Rapid Development Period (2012-2015)	Transformation and Upgrading Period (2016 to now)
Business Type	Mainly fruits, supplemented by vegetables.	Mainly fruits, while meat, eggs, milk, flowers, vegetables, aquatic products are gradually increasing.	Fruits, flowers, meat, eggs, milk, aquatic products, seafood, and vegetables.
Development Characteristics	Mainly regional vertical e-commerce is developing slowly.	Capital inflows and category segmentation have driven leading platforms to dominate, spurring rapid growth in fresh e-commerce.	Many small and medium fresh e-commerce firms exited, while giant enterprises expanded cold-chain investment; pandemic-driven demand further accelerated growth.
Business Model	City central warehouse model	City center warehouse model, front warehouse model	City central warehouse model, front warehouse model, warehouse and cushion integrated model, community group buying model, freezer self-pickup model, etc.
Representative Enterprise	Yiguo Fresh, Tootoo, Cai Guanxia, Youcai.com, Womai.com, etc.	Benlai.com, Tmall Fresh, JD Fresh, Yonghui Superstores, SFbest.com, Dmall, etc.	Freshippo, Dingdong MaiCai, MISS Fresh, JD Home, 7FRESH, Taocaicai, Meituan MaiCai, etc.

Source: Development of E-commerce of Fresh Agricultural Products in China: Progress, Difficulties and Strategies (Jiu et al., 2020)

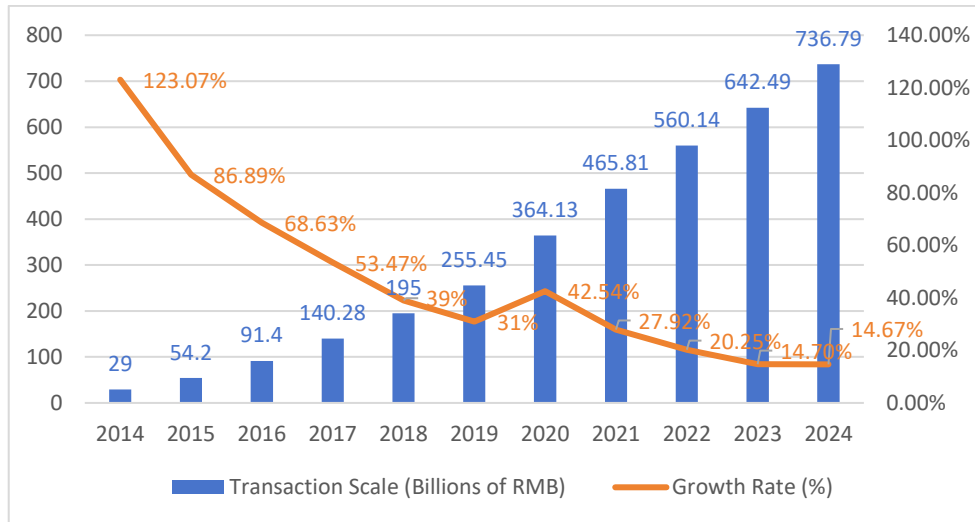


Figure 1.1: China's Fresh E-commerce Transaction Scale and Growth Rate (2014-2024)

Source: 2024 China Fresh E-commerce Market Data Report (Network Economy Society, 2025)

Fresh e-commerce represents an emerging segment within the e-commerce domain, driving innovation in the online market, transforming its landscape, and reimagining the distribution of agricultural products. According to data from China's National Bureau of Statistics, China's total online retail sales reached 15.4264 trillion yuan in 2023. Meanwhile, the transaction volume of China's fresh e-commerce was 642.49 billion yuan, making up 4.16% of the overall online retail sales. This indicates that, compared to overall e-commerce, fresh e-commerce still occupies only a small portion of online transactions. However, fresh e-commerce still has broad prospects for the future.

1.2.2 Policy Background of Chinese Fresh E-commerce

On February 3, 2024, the Chinese central authorities released a collaborative statement by the Central Committee of the Communist Party of China and the State Council, entitled "Guidance on Adopting and Replicating the Achievements of the 'Thousand Villages Showcase and Ten Thousand Villages Rejuvenation' Initiative to Effectively Advance Comprehensive Rural Revitalization." This marks the 21st consecutive year since

2004 that a central document has been issued with a focus on agriculture, rural areas, and farmers.

In recent years, e-commerce has been repeatedly mentioned in these central documents. In 2022, regions were incentivized to enhance the versatility of agriculture, harness the potential of rural areas, and give precedence to the growth of sectors like agro-processing, rural recreational tourism, and e-commerce in rural settings. In 2023, there was an emphasis on implementing projects like “commercial agriculture” and “Internet +” to promote agricultural products from villages to cities through models like direct sourcing and personalized manufacturing in the realm of agricultural products e-commerce.

China unveiled its “No. 1 central document” for 2024, focusing on promoting comprehensive rural revitalization by learning from experiences gained through large-scale projects. It systematically deploys efforts towards “agriculture, rural areas, and farmers” both presently and for future periods, while proposing several policy measures aimed at ensuring national food security and improving rural industry development levels. Industrial revitalization is prioritized within this context. Regarding rural industrial development, the document once again highlights e-commerce and live broadcasting. This is also where it introduces, for the first time, a high-quality development project specifically targeting rural e-commerce.

Presently, the evolution of rural e-commerce in China has advanced from the initial introduction of express delivery services to rural locations, through the upward flow of agricultural produce, and ultimately towards digital transformation. It has now embarked on a new phase of high-quality development, characterized by increasingly diverse operational

models. Fresh e-commerce has emerged as a significant element within the realm of agricultural product e-commerce (Gao & Sun, 2019).

By 2022, China's fresh e-commerce market transaction scale had reached 921.24 billion yuan, with a growth rate of 37.25%. The emergence of fresh food suppliers has promoted supply-side reform for traditional agricultural products and accelerated adjustments in the agricultural industrial structure (Chen, 2024). The circulation of fresh agricultural products not only affects the livelihoods of millions of farmers but also impacts public quality of life; it is therefore a hot social issue related to the national economy and people's well-being (Wang & Zhang, 2016).

1.2.3 Major Business Models of Fresh E-Commerce in China

The rapid development of the Internet and the rapid rise of fresh e-commerce have led a number of entrepreneurial teams and Internet giants to explore different models. Currently, the main modes and representative companies of fresh e-commerce include (Liu & Hu, 2023): comprehensive e-commerce such as JD Fresh, Tmall Fresh, Benlai.com, etc.; the front warehouse mode represented by Dingdong MaiCai, Pupumall, etc.; the store-warehouse integration mode (to the store + to the home) exemplified by Yonghui Superstores, Freshippo, etc.; and the community group purchase mode including Taocaicai, XingSheng Selected, etc. As shown in Table 1.2.

Comprehensive e-commerce model refers to the expansion of traditional e-commerce platforms into the fresh e-commerce category. Utilizing the original online shopping system and logistics network, these platforms provide customers with sales and distribution of fresh e-commerce goods. This model mainly involves attracting fresh food manufacturers to settle on their platforms, with cold chain distribution being the

responsibility of the resident merchants, while the platform is only responsible for supervision.

Table 1.2: Main models of China's Fresh E-commerce in 2023

Business model	Representative Fresh E-commerce
Comprehensive E-commerce	Tmall Fresh, JD Fresh, Benlai.com
Front Warehouse	Dingdong MaiCai, Miss Fresh, Pupumall, MeiTuan MaiCai
Store-warehouse Integration	Yonghui Superstores, Freshippo, 7Fresh
Community Group Purchase	Taocaicai, XingSheng Selected, ShiHang Fresh

Source: Evolution, Characteristics and Driving Mechanism of Fresh Produce E-commerce Model (Liu & Hu, 2023)

Front Warehouse model is a warehouse distribution model designed to solve the distribution challenges of fresh e-commerce. The key feature of this model is that the warehouse is located near the community where consumers are concentrated, typically no more than 3 kilometers away. This setup aims to reduce delivery time and improve delivery efficiency, thereby minimizing the loss of fresh products. In the Front Warehouse operation mode, the city warehouse is responsible for supply, and riders pick up the goods from the Front Warehouse for delivery.

Store-warehouse Integration, also known as the “store + home” model, encompasses two types: online-to-offline expansion and the opening of offline superstores for home delivery services. The former is represented by Freshippo and 7Fresh, while the latter is represented by Yonghui Superstores. In this model, the store serves not only as a retail outlet but also as an online warehousing and distribution center. Consumers can shop in-store or

order online, with the platform providing delivery services within an hour to users within 1-3 kilometers of the store.

Community Group Purchase is a shopping approach that combines “online ordering + supplier delivery + group management,” with the community as its core. Consumers place orders through the group leader’s recommendation or directly on the platform. The platform provides the product supply chain logistics and after-sales service, and delivers the goods to a designated pick-up point in the community the next day for consumer self-pickup.

1.2.4 Current Situation of Service Quality in China’s Fresh E-commerce

As the demand for fresh e-commerce shopping surges, industry competition continues to intensify. By the close of 2022, the cumulative count of registered enterprises engaged in fresh e-commerce in China amounted to 27,715, marking a nearly threefold increase compared to the figure in 2017 (Ma, 2024). Fierce market competition and rapid development have led to multiple difficulties for the fresh e-commerce industry, such as weak profitability, poor platform management, difficulty in ensuring product quality, and intensified homogeneous competition, seriously restricting its sustainable development.

Major fresh e-commerce platforms rely mainly on holiday promotions, points, group discounts, and other pricing strategies to maintain daily active users and repeat purchase rates. Industry research (Xiang & Cui, 2022) indicates that leading platforms such as Dingdong Maicai, MissFresh, and Meituan Maicai utilize targeted pricing tactics for customer acquisition and retention. For example, Dingdong Maicai and Meituan Maicai implement task-based reward systems to encourage repeat purchases, while MissFresh adopts a group leader model that provides commissions to increase order frequency. These platforms also offer membership programs featuring benefits like free delivery and exclusive

coupons to enhance user engagement. Data shows Dingdong Maicai achieves particularly strong performance in new user retention. The platforms employ distinct pricing approaches: Meituan Maicai emphasizes affordability through subsidies, Dingdong Maicai maintains a balance between low-margin staples and premium products, and MissFresh focuses on high-value discount offerings.

In recent years, the volume of complaints pertaining to fresh e-commerce has exhibited an annual upward trajectory. In 2020, China's 12315 platform (a special telephone line for consumer complaints and reports) received a total of 65,800 complaints and reports related to online purchases of fresh e-commerce food (Kong, 2021). According to the 2024 annual report released by the Chinese consumer dispute mediation platform Diansubao, a total of 233 internet consumption platforms were involved in consumer complaints throughout the year (Diansubao, 2025). Among them, fresh e-commerce platforms were frequently reported for issues such as spoiled goods, delayed deliveries, misleading promotions, and poor after-sales service, indicating persistent weaknesses in service quality management. According to the Shenzhen Municipal Consumer Council, from January 1 to November 10, 2022, a total of 1,704 complaints about fresh e-commerce were filed in just one city in China, Shenzhen, representing a 77.32% increase compared to the same period last year (Huang, 2022). Fresh e-commerce services have been criticized for common issues such as the quality of goods, refunds, shipments, order problems, and false promotions.

Comparing Avery Consulting's 2017 and 2019 surveys on fresh e-commerce (see Figure 1.2 and Figure 1.3), it can be seen that in 2017, consumer satisfaction was lower mainly due to logistics and distribution, price, APP design, and experience; and in 2019, the top three factors that consumers considered when purchasing fresh e-commerce online were

safety, quality, and taste, followed by price and ease of purchasing in descending order. The factors that customers consider in fresh e-commerce services are changing over time (Yao, 2020).

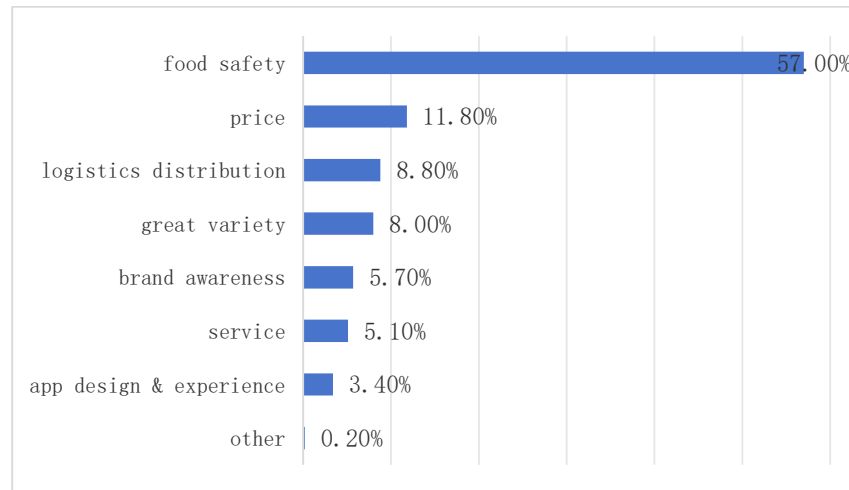


Figure 1.2: Key Factors for Consumers Buying Fresh Food Online in 2017
Source: Data are derived from the *China Fresh E-commerce Industry Research Report 2018*, published by Avery Consulting Research Institute

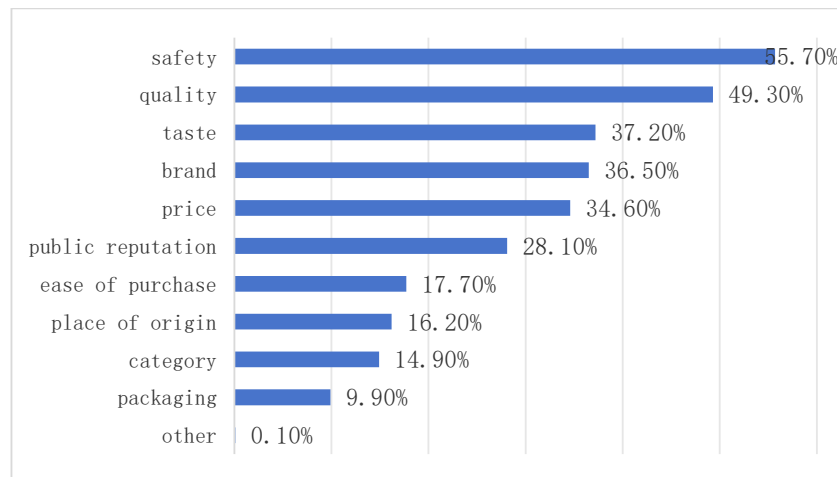


Figure 1.3: Key Factors for Consumers Buying Fresh Food Online in 2019
Source: Data are derived from the *China Fresh E-commerce Industry Research Report 2019*, published by Avery Consulting Research Institute

A thorough review of multiple research studies on the determinants affecting customer satisfaction in e-commerce indicates varied and inconsistent findings. These inconsistencies can be attributed to differences in context, research design, data sources, and

research methods used in these studies. Differences between fresh e-commerce and traditional e-commerce need further study and clear E-Service Quality assessment.

1.2.5 Online Consumer Reviews

To meet the demand of consumers who wish to provide feedback after purchases and to offer reference opinions for other consumers, e-commerce platforms permit customers to share their firsthand experiences by posting product reviews or comments on their portals. Typically, reviews can provide insights into product attributes and supplier attitudes, as they represent authentic customer sentiments post-purchase (Song et al., 2013). Customer reviews serve as a centralized hub for consumers' honest opinions, mainly in the form of images and text, and this data can serve as a crucial reference.

A popular product may attract hundreds or thousands of reviews. With the dramatic expansion of review information, the time it takes for users to capture and perceive this information from the massive online review resources increases exponentially, making it difficult for fresh e-commerce companies to track and manage customer opinions. Most of these massive comments contain users' subjective emotions, which are rich in practical significance and commercial value waiting to be explored.

Customers evaluate the performance of a product using emotional statements, representing their feeling of satisfaction when they are pleased with their purchase (Howard & Sheth, 1969). Customer satisfaction, based on an experience-based consumer attitude, effectively and fully expresses their degree of preference. In e-commerce environments, a large number of online reviews can serve as a data source for predicting repeat purchase intentions. For example, Suryadi (2020) proposed a machine learning-based approach to

predict repeat purchase intentions based on online customer reviews, aiming to gain insights from the vast amount of available data.

According to the expectation confirmation model, measuring customer satisfaction involves measuring the gap between “customer expectations” and “perceived value” (Angelovska, 2023). To comprehend the essence of customer satisfaction, it is crucial to grasp “customer loss,” the gap between the “reality that the customer reluctantly accepts” and their “real need.” Customer comments highlight this gap and loss. Customer feedback offers abundant information that mirrors consumers’ attributes and their levels of satisfaction with the provided services (Oh et al., 2022). Therefore, the service experience mentioned in customer reviews indicates the main attributes and quality levels of the product or service that customers consider (Kim & Kim, 2022).

Consumer feedback, comprising both complaints and compliments, has traditionally served as an important source of feedback on company performance. Essentially, such feedback acts as an exception-reporting mechanism, highlighting areas that need improvement or further strengthening. Given that customers invest their time and effort in articulating their experience with an online service, this indeed emphasizes the significance of these attributes in the post-usage evaluation process. While customers’ comments may not necessarily encompass their entire experience with a provider, they highlight the most important dimensions and precise attributes of service quality. Consequently, examining consumer complaints and compliments proves to be particularly helpful in delving into the various aspects related to customer-perceived service quality.

The initial step in devising strategies to improve service quality is to listen to customers. Although recent studies (Kang & Namkung, 2024; Lee et al., 2022; Yang et al.,

2024) employed structured questionnaires with scale items derived from established models such as the E-S-QUAL framework (Parasuraman et al., 2005), the Technology Acceptance Model (TAM) (Davis, 1989), and E-TailQ (Wolfenbarger & Gilly, 2003), these instruments were originally designed for general e-commerce settings and do not capture the specific operational characteristics of the fresh grocery sector, including perishability, cold-chain logistics, and delivery timeliness. Respondents with tertiary education (bachelor's degree or higher) consistently exceed 60% in online survey samples (Su et al., 2022; Zhang et al., 2025), resulting in insufficient coverage of populations with lower educational attainment. Moreover, social desirability bias often causes participants to overreport satisfaction or underreport negative experiences, particularly in self-administered surveys (Durmaz et al., 2020). For example, Park et al. (2018) found that in Samsung's online chat service, users who did not leave feedback were more likely to be dissatisfied than those who did, suggesting that survey-based methods may underestimate the actual proportion of customer dissatisfaction.

Unlike surveys based on predefined questions and fixed response scales, customer reviews are naturally occurring and non-prompted feedback. This type of data helps reduce response bias, particularly the common positive bias found in surveys. For instance, Pan (2024) analyzed customer reviews of a flagship fresh e-commerce store using word frequency and semantic network analysis and identified five core satisfaction factors: service, product quality, logistics, packaging, and price, demonstrating that reviews provide broader insights than structured survey data.

Customer reviews often contain spontaneous emotional expressions, detailed experiential narratives, and emergent issues that are difficult to capture through prestructured

questionnaires. For example, Guan et al. (2022) developed a hybrid model combining Latent Dirichlet Allocation (LDA), Structural Equation Modeling (SEM), and Extreme Gradient Boosting (XGBoost) to analyze user reviews of fresh e-commerce platforms during the COVID-19 pandemic. Their findings revealed that factors such as delivery timeliness, logistics speed, and product freshness had significant impacts on customer satisfaction dimensions that are often overlooked in conventional surveys. With text mining techniques like topic modeling and aspect-based sentiment analysis, researchers can systematically extract key service quality dimensions and their associated emotional tones. For instance, Yang (2025) used LDA to analyze reviews on JD Fresh and uncovered detailed logistics-related service aspects, including reliability, convenience, and safety guarantees. They further applied sentiment and spatiotemporal analysis to show how customer perceptions of these dimensions varied by region and season.

Unlike traditional surveys that often gather a few hundred to a few thousand responses at high cost and effort, review-based studies in fresh e-commerce commonly involve datasets of 10,000 to over 100,000 reviews (Deniz et al., 2022). This enables broader sample coverage across different regions, backgrounds, and consumer segments.

1.3 Problem Statement

The field of Service Quality and E-Service Quality has been extensively explored in the literature, with numerous articles published on the subject since the seminal paper by Parasuraman et al. (1988). Nevertheless, there exists a variety in the way service quality is conceived, measured, and researched. Diverse categories of e-services correspond to varying user requirements, leading to distinct dimensions and metrics of E-Service Quality for each type (Wang et al., 2019). E-Service Quality assessments should be considered within the

context of diverse nationalities and cultures (Ghosh, 2018). Not all E-Service Quality scales are suitable for fresh e-commerce, and the selection of the most appropriate scale must depend on the specific research context (Morsi, 2023). While the Service Quality Model covers basic categories of service quality elements, it lacks specific quality elements tailored to individual industries. This means that quality components depend on the specific context being discussed (Shokouhyar et al., 2020).

Some studies have proposed scales that encompass multiple dimensions, such as information quality, service interaction quality, and website usability (Cao et al., 2024; Ighomereho et al., 2022; Wijaya et al., 2021). However, consensus has not yet been reached on the classification of these dimensions or their universal applicability. Regarding the sourcing of data, the majority of scholars rely on questionnaire surveys as their primary means of collecting information. In contrast, the utilization of customer post-purchase reviews for data acquisition is still in its infancy. Despite relying on customer review texts as data sources, prior research has often focused on only one fresh e-commerce platform, such as JD Fresh (Xu & Chen, 2020) , potentially resulting in non-representative findings. China's fresh e-commerce transaction volume reached CNY 736.79 billion in 2024, a 14.67% year-on-year increase (Network Economy Society, 2025). As pointed out by (Zhang, 2023), the Chinese fresh e-commerce market consists of multiple operational models and platform types, including comprehensive e-commerce (e.g., JD Fresh, Tmall Fresh), front warehouse (e.g., Dingdong MaiCai, Pupumall), store-warehouse integration (e.g., Yonghui Superstores, Freshippo), and community group purchase (e.g., Taocaicai, XingSheng Selected). Each model differs significantly in terms of logistics design, delivery structure, and consumer interaction. Therefore, focusing exclusively on a single platform risk overlooking the structural diversity and varying service experiences across the broader industry landscape.

Most research suggests that service quality exerts a direct and favorable influence on customer satisfaction. Nevertheless, variations are observed in the degree to which various aspects of service quality affect customer satisfaction. Xu and Chen (2020)'s research findings provide support for the conclusion that customer satisfaction is notably influenced by the tangibility, reliability, empathy, and responsiveness of service quality. According to the study by Guan et al. (2022), factors such as logistics, products, platforms, and epidemics play a key role in influencing consumer satisfaction. According to Liu et al. (2023), from the product perspective, factors such as product quality and pricing have considerable impacts on consumer satisfaction. On the service side, perceived usability, reliability, responsiveness, and convenience play significant roles. Additional studies are required to elucidate which particular aspects of service quality exert substantial influences on customer satisfaction.

Moreover, customer satisfaction and repurchase intention are two essential outcomes for evaluating the effectiveness of service delivery, yet empirical research in fresh e-commerce often fails to link these variables to context-specific service quality dimensions. Most research tends to concentrate on examining the dyadic connections among these three constructs, for instance, the link between service quality and customer satisfaction, or the association between customer satisfaction and repurchase intention (Liu et al., 2023; Sun, 2021), while lacking in-depth construction and analysis of an overall relational model among the three. It is widely acknowledged in the scholarly works that service quality has a direct positive effect on customer satisfaction; namely, the better the service quality provided by a company, the higher the customer satisfaction. Furthermore, customer satisfaction directly influences the intention to repurchase, with customers who are more satisfied being more likely to purchase the company's products or services again. However, despite the widespread acknowledgment of the direct connections between service quality and customer

satisfaction, and between customer satisfaction and repurchase intention, there is still a paucity of in-depth research investigating whether service quality directly influences repurchase intention, and whether customer satisfaction acts as a mediator in this relationship.

In the e-commerce environment, repurchase intention is a powerful predictor of website customer retention (Koufaris, 2002). While customer repurchase intention (RI) is widely recognized as a key driver of long-term profitability for e-commerce platforms, it remains a persistent challenge in the context of fresh e-commerce. The inherently low switching costs of online platforms, combined with the highly competitive nature of the industry, make it difficult for platforms to retain customers over time. Moreover, the perishability of fresh products, variability in delivery experience, and inconsistency in service quality across regions further complicate customer retention efforts. Existing studies often focus on general e-commerce or limited-service attributes, leaving a gap in understanding the specific service quality drivers that influence RI in the fresh food sector. Therefore, a deeper investigation into the service quality–satisfaction–RI linkage is needed to help platforms develop targeted strategies for improving customer loyalty.

In light of these gaps, this study aims to explore these uncertainties further, grounded in the fresh e-commerce industry in China, to investigate the multiple dimensions of service quality empirically and to clarify both the direct and indirect effects of these dimensions on customer satisfaction and repeat-purchase intention.

1.4 Research Questions

- i. What is the relationship between service quality and customer satisfaction?

- ii. What is the relationship between service quality and customer repurchase intention?
- iii. What is the impact of consumer satisfaction on repurchase intention?
- iv. Does consumer satisfaction have a mediating role between the association of service quality and consumer repurchase intention?

1.5 Objectives

To obtain a thorough insight into the facets of service quality and the complex interplay between service quality, customer satisfaction, and repurchase intention within China's fresh e-commerce, this study sets forth the following objectives. The subsequent content will detail both the overall and specific aims of this research.

1.5.1 Overall Objective

This research aims to comprehensively examine the dimensions of service quality in China's fresh e-commerce, assess how these dimensions influence consumer satisfaction and repurchase intention, and investigate the mediating effect of consumer satisfaction.

1.5.2 Specific Objective

The specific aims of the research are:

- i. To investigate the impact of service quality towards consumer satisfaction.
- ii. To examine the impact of service quality towards consumer repurchase intention.

- iii. To explore the impact of consumer satisfaction on consumer repurchase intention.
- iv. To assess the mediating impact of consumer satisfaction on service quality and consumer repurchase intention.

1.6 Significance of the Study

This study provides a contextual extension and an external validity assessment of service quality theory within China's fresh e-commerce setting. By specifying and empirically testing the mechanism linking service quality, customer satisfaction, and repurchase intention, it distinguishes the direct effects of individual service quality elements from the indirect effects that operate through satisfaction, thereby clarifying the theory's applicability and boundary conditions in contexts characterized by high purchase frequency, product perishability, and reliance on cold chain logistics. The findings offer a new analytical lens and evidentiary base for consumer behavior and marketing, and they provide a reusable theoretical framework and measurement approach for subsequent research, advancing the development of service quality theory in the Chinese fresh e-commerce domain.

Unlike previous studies that rely primarily on survey data or traditional SERVQUAL-based models, this study adopts a novel mixed-method approach by integrating topic modeling and sentiment analysis on large-scale customer review data from multiple Chinese fresh e-commerce platforms. This enables a more data-driven and fine-grained identification of service quality dimensions that better reflect actual customer perceptions. Furthermore, the study constructs and empirically tests a structural equation model to explore the relationships among service quality, customer satisfaction, and repurchase intention, with customer satisfaction serving as a mediating variable. These

methodological and contextual innovations provide fresh perspectives to the literature on e-commerce service quality.

From a practical perspective, this research has significant practical implications for fresh e-commerce enterprises. The study reveals which service quality dimensions positively impact consumer satisfaction and repurchase intention, helping enterprises optimize their service processes and enhance customer satisfaction and loyalty. Furthermore, by verifying the mediating role of consumer satisfaction in the influence of service quality on repurchase intention, enterprises can gain deeper insights into the psychological mechanisms behind consumer behavior, thus enabling the formulation of more effective marketing strategies and customer relationship management programs.

In addition to its significance for enterprises, this research also has profound implications for governments. This research underscores the importance of service quality in the fresh e-commerce industry, providing valuable insights that can help governments formulate effective policies and strengthen regulatory frameworks. By identifying key dimensions, governments can ensure that consumers receive high-quality services, thereby fostering consumer trust and confidence in the digital economy. These efforts will not only protect consumer rights but also promote the sustainable growth of fresh e-commerce, contributing positively to the overall economic landscape.

For consumers, this research provides a clearer picture of what constitutes excellent service in the fresh e-commerce space. By understanding the factors that influence their satisfaction and repurchase intention, consumers can make more informed choices about which platforms to use. Additionally, this research emphasizes the role of consumer satisfaction as a critical mediator, encouraging consumers to prioritize their own experiences

and expectations when engaging with fresh e-commerce platforms. Ultimately, this leads to more satisfying and rewarding shopping experiences, thereby enhancing overall consumer well-being.

1.7 Scope of Study

The research will focus on Chinese fresh e-commerce, excluding companies operating in other countries. It will examine businesses working in four different modes: comprehensive e-commerce, front warehouse mode, store-warehouse integration mode, and community group purchase mode. The selection of the four major fresh e-commerce models is based on both theoretical classification (Liu & Hu, 2023; Zhang, 2023) and their demonstrated market relevance. Community group purchase has experienced rapid growth in recent years, with its market size increasing from approximately RMB 72 billion in 2020 to RMB 300 billion in 2021, making it a key force in the post-pandemic grocery landscape (Jing, 2021; Song et al., 2023). Platforms such as Taocaicai, Xingsheng Youxuan, and Meituan Youxuan have played pivotal roles in scaling this model across lower-tier markets. Comprehensive e-commerce platforms like JD Fresh and Tmall Supermarket remain dominant players in the sector, as business-to-consumer (B2C) platforms accounted for over 88% of China's total e-commerce market in 2024 (Mordor Intelligence, 2025). According to the Chinese Academy of International Trade and Economic Cooperation (2024), Front warehouse models, represented by Dingdong Maicai and MissFresh, serve as the core of the growing instant retail segment, which is projected to surpass RMB 2 trillion shortly due to rising demand for ultrafast delivery. The store-warehouse integration model, which merges physical retail with instant delivery, is becoming a key fulfillment approach in China's fresh e-commerce. Represented by Yonghui Superstores and Hema Fresh, it transforms traditional stores into hubs for both shopping and last-mile distribution. The Yonghui Group's online

sales reached RMB 7.92 billion in the first half of 2023, reflecting a year-on-year growth of 4.4%. As of August 2023, Yonghui had established 652 integrated store-warehouse units across 181 cities in China (Yonghui Superstores Co., 2023). Collectively, these four models encompass distinct fulfillment structures, target different consumer segments, and reflect the evolving demands and logistics innovations within China's fresh e-commerce ecosystem. The review data were collected between August 2023 and August 2024, allowing for seasonally and behaviorally diverse observations across these platforms.

The data analyzed in this research will be restricted to customer review texts for popular products sold on these targeted e-commerce platforms. By focusing on this specific data source, the research aims to capture authentic and spontaneous feedback from customers, thus providing a more accurate reflection of their experiences and perceptions.

The research will center on three core variables: various dimensions of service quality, customer satisfaction, and customer repurchase intention. By narrowing the scope to these variables, the research can more effectively explore the relationships and interactions among them, offering more profound insights into the factors that drive customer loyalty and satisfaction in Chinese fresh e-commerce.

1.8 Operational Definitions

This section presents the operational definitions of the core constructs used in this study. All definitions are derived from existing scholarly literature to ensure conceptual clarity and consistency throughout the research.

1.8.1 Fresh E-Commerce

Fresh e-commerce refers to an online retail format specializing in the sale and distribution of perishable agricultural products, such as fruits, vegetables, meat, eggs, and seafood (Jiang et al., 2021). It is characterized by time sensitivity, reliance on cold-chain logistics, and strict quality control mechanisms (Ma et al., 2022).

1.8.2 E-Service Quality

E-service quality refers to consumers' overall perception of the effectiveness and efficiency of service delivery in an online environment. It encompasses multiple dimensions including system reliability, responsiveness, ease of use, and service fulfillment (Ighomereho et al., 2022; Zeithaml, 2000).

1.8.3 Fulfillment

Fulfillment refers to the extent to which e-commerce platforms deliver products as promised in terms of order accuracy and the condition of goods upon receipt (Lin et al., 2021; Parasuraman et al., 2005). In the fresh e-commerce context, fulfillment primarily relates to delivering the right items on time and in undamaged condition.

1.8.4 Logistics Service Quality

Logistics Service Quality (LSQ) is defined as customers' perception of the performance of logistics services across multiple dimensions, including timeliness, order condition, discrepancy handling, information quality, personnel contact quality, and procedural efficiency (Mentzer et al., 2001). It reflects how well logistics services meet customer expectations in the ordering and delivery process.

1.8.5 Ease of Use

Ease of use refers to the extent to which consumers perceive both the e-commerce platform and the purchased products as simple, intuitive, and convenient to use (Davis, 1989). In the fresh e-commerce context, this includes not only ease of navigating the platform, such as product search, ordering, and tracking, but also the convenience of using the products themselves, such as clear instructions, easy storage, and user-friendly packaging.

1.8.6 Customer Service

Customer service in the e-commerce context encompasses all forms of assistance provided before, during, and after a transaction. This includes complaint resolution, return management, and real-time customer communication via chatbots or human agents (Parasuraman et al., 1988; Wattoo et al., 2025). For fresh e-commerce, responsive and reliable customer service is vital in addressing concerns such as spoilage, delays, or refund issues.

1.8.7 Economic Efficiency

Economic efficiency is conceptualized as consumers' perception of value for money, which refers to an evaluation of affordability, discount effects, and overall cost–benefit trade-offs (Zeithaml, 1988). Empirical studies further show that perceived affordability and discount availability enhance perceived value (Lee & Chen, 2018), while overall perceived value in fast-paced e-commerce settings significantly increases purchase intention (Wang et al., 2023).

1.8.8 Customer Satisfaction

Customer satisfaction refers to the customer's overall evaluation of a purchase and use experience, formed through a comparison between the actual outcomes and the expectations held prior to the transaction (Oliver, 2010). It is conceptualized as the result of cognitive assessment regarding the perceived balance between the rewards and costs of the purchase in relation to anticipated consequences (Churchill & Surprenant, 1982). It reflects the perceived balance between the costs and rewards of the transaction.

1.8.9 Repurchase Intention

Repurchase intention refers to an individual's judgment regarding the likelihood of purchasing a specific product or service again from the same provider, based on prior experience, current circumstances, and anticipated future conditions (Hellier et al., 2003; Mittal & Kamakura, 2001). It reflects the perceived possibility that a customer will return to the same vendor for future purchases (Fang et al., 2014).

1.9 Summary

In this chapter, a holistic perspective on the study has been presented. This includes an exploration of its foundational background, a clear problem statement that identifies knowledge gaps, the study's overarching aim, precisely defined research objectives, thoughtfully crafted research questions, the profound significance of the study, and its clearly defined scope. The subsequent chapter delves into the literature review and introduces the pivotal concepts that underpin this research endeavor.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter offers a system review of research on service quality in fresh e-commerce and its connection to customer satisfaction and repurchase intention. Studies were identified through structured searches of Scopus, Web of Science, IEEE Xplore, and ScienceDirect, using terms such as “e-commerce,” “e-service quality,” “customer satisfaction,” “repurchase intention,” “customer review,” and “aspect-based sentiment,” supplemented by backward and forward citation chasing, focusing on work published since 2020. To clarify mechanisms and boundary conditions, the review compares both convergent and divergent findings. In the usability pathway, one stream shows that perceived ease of use and perceived usefulness increase satisfaction and, consequently, repurchase intention (Nuralam et al., 2024), while another stream suggests that ease of use influences repurchase indirectly through utilitarian value and prior experience (Imbayani et al., 2025). On the distinction between process and outcome, classical e-service frameworks locate delivery performance within fulfillment (Parasuraman et al., 2005), whereas fresh-grocery studies separate logistics service quality from fulfillment to reduce conceptual overlap and better capture perishable supply requirements (Yang et al., 2024). In the domain of economic efficiency, evidence links price fairness to repurchase mainly through satisfaction in cross-border settings (Do et al., 2023), while other work emphasizes a direct role for customer perceived value in repurchase decisions (Wu et al., 2023). Section 2.2 defines broad concepts and reviews five established dimensions of e-service quality, fulfillment, logistics service quality, ease of use, customer service, and economic efficiency, followed by focused

discussions of customer satisfaction (Section 2.2.2) and repurchase intention (Section 2.2.3). Section 2.3 outlines underpinning theories, Section 2.4 sets out the conceptual framework, Section 2.5 develops the hypotheses, and Section 2.6 summarizes implications for the empirical analysis.

2.2 Broad Concepts

The key themes, concepts, or variables of importance within the researcher's field of study were discussed in more depth in this section.

2.2.1 E-Service Quality

Service quality is commonly defined as customers' overall judgment of service excellence and is grounded in the expectation–confirmation paradigm (Grönroos, 1984; Oliver, 1980; Parasuraman et al., 1988). Within this stream, SERVQUAL operationalizes quality as the perceived–expected gap and was refined from ten initial dimensions to five core dimensions: reliability, responsiveness, assurance, empathy, and tangibles (Parasuraman et al., 1988; Parasuraman et al., 1985). This framework has been highly influential in face-to-face service settings rich in physical touchpoints and has provided a foundation for subsequent online measurement.

As transactions have migrated online, research attention has shifted to electronic service quality (e-service quality), namely how online platforms enhance the efficiency and effectiveness of customers' browsing, selection, ordering, and fulfillment processes (Fassnacht & Koese, 2006; Gummerus et al., 2004; Zeithaml, 2000). Unlike offline contexts, quality perceptions online are co-determined by front-end interfaces (usability) and back-end processes (fulfillment, logistics, post-purchase service). Directly transplanting traditional scales, therefore, risks incomplete coverage and blurred boundaries. Empirical e-

service studies have proposed recurring configurations such as efficiency/system availability, website design/ease of use, fulfillment/reliability, privacy/security, and responsiveness/contact/customer service (Blut et al., 2015; Jiang et al., 2016; Kalia & Paul, 2021; Ladhari, 2010a; Lee & Lin, 2005; Parasuraman et al., 2005; Rita et al., 2019; Santos, 2003; Yen & Lu, 2008). While labels and granularity vary across studies, the literature converges on four broad clusters: usability, fulfillment, customer service, and privacy/security.

However, fresh ecommerce differs significantly from general online retailing in its technical and operational aspects: perishability, time sensitivity, reliance on a cold chain, higher spoilage risk, and a purchasing pattern characterized by frequent orders and low average order value. These features shift customers' main concerns and how they evaluate products. The importance of delivery quality and outcome conformance becomes more apparent earlier, and consumers become more sensitive to price, shipping fees, and refund policies.

Consistent with this perspective, recent research on fresh ecommerce consistently emphasizes the importance of logistics and delivery, including the cold chain and protective packaging, fulfillment outcomes like freshness and product integrity, and economic efficiency involving price fairness, promotional access, and overall costs (Hou & Wang, 2022; Lee et al., 2020; Lin, 2020; Ma & Li, 2020; Zhu & Wang, 2024). This suggests that even within an electronic service quality framework, the fresh category requires redefining specific dimensions to prevent mixing process quality, such as cold chain reliability and timeliness, with outcome quality, like freshness and consistency between the order and

delivered items. It also calls for explicitly including a value-based approach to economic efficiency as a key dimension in high-frequency online purchasing environments.

Table 2.1: Literature Baseline on E-service Quality

Author	Dimensions	Number of Dimensions	Method
Santos (2003)	Reliability, Efficiency, Support, Communication, Security, Incentive	6	30 Focus Groups
Parasuraman et al. (2005)	Efficiency, System Availability, Fulfillment, Privacy	4	Questionnaires from Consumers of Amazon.com and Walmart.com
Lee and Lin (2005)	Website Design, Reliability, Responsiveness, Trust	4	305 Questionnaires from Online Consumers
Yen and Lu (2008)	Efficiency, Privacy Protection, Contact, Fulfillment, Responsiveness	5	Questionnaires of 619 bidders in the online auction (Yahoo! KiMo)
Ladhari (2010a)	Reliability/Fulfillment, Responsiveness, Web Design, Ease of Use/Usability, Privacy/Security, Information Quality/Benefit	6	Literature Review
Blut et al. (2015)	Website Design, Fulfillment, Customer Service, Security/Privacy	4	Meta-Analysis of Literature between 2000 and 2014
Jiang et al. (2016)	Care, Reliability, Products Portfolio, Ease of Use, Security	5	Survey Of 235 Online Customers
Rita et al. (2019)	Website Design, Security/Privacy, Fulfillment	3	Survey of 355 Indonesian Online Consumers
Kalia and Paul (2021)	Efficiency, Fulfillment, System Availability, Privacy, Responsiveness, Compensation, Contact	7	Survey of 300 Consumers on Five Leading E-retailers in the Indian market

Table 2.1 continued

Lee et al. (2020)	System Quality, Product Quality, Brand Characteristics, Economic Efficiency	4	Survey of 309 Korean Fresh Food Online Consumers
Lin (2020)	Product Quality, Brand Image, Website Quality, Logistics and Distribution, After-Sales Service	5	368 Questionnaires from Chinese Consumers in Fresh E-Commerce
Ma and Li (2020)	Logistics, Product Quality, Packaging, Price, After-Sales Service	5	Online Review Text Data of Fresh Food Products on China's JD Fresh
Wang (2021)	Product Selection & Sourcing, Shopping Convenience, Product Quality, Entertainment Experience, Website Trust	5	394 Questionnaires from Chinese Customers Who Purchase Fresh Agricultural Products Online
Hou and Wang (2022)	Product Quality, Ease of Use, Usefulness, Perceived Risk, Customer Care, Security, Packaging, and Logistics	7	258 Questionnaires from Chinese Customers in Fresh Agricultural E-Commerce
Zhu and Wang (2024)	Visibility, Reliability, Responsiveness, Convenience, Ease of Use	5	335 Questionnaires from Chinese Customers

Building on the evidence in Table 2.1, this study adopts the principles of semantic consolidation, contextual retention, and redundancy elimination to develop a service quality framework for fresh ecommerce with five dimensions. The framework is shown in Table 2.2.

The dimension-mapping table (Table 2.2) consolidates the heterogeneous and inconsistently named e-service quality dimensions reported across prior studies into five higher-order constructs suitable for fresh food e-commerce: Fulfillment, Logistics Service Quality, Ease of Use, Customer Service, and Economic Efficiency. Source material is drawn from the literature baseline (Table 2.1), which systematically records each representative

study's context, original dimensions, number of dimensions, and research method/sample, thereby providing the evidential basis for consolidation. Building on Table 2.1, original dimensions and their operational definitions were extracted study by study with terminology and context preserved, then normalized through synonym harmonization. Specifically, Website design/Usability/Efficiency/System availability were grouped under the Ease of Use/in-use assurance cluster; Reliability/Fulfillment together with fresh-context Product quality (delivery condition/freshness/intactness) under Fulfillment; Logistics/Logistics & distribution/Packaging and logistics under Logistics Service Quality; Support/Communication/Contact/Responsiveness/After-sales/Customer care under Customer Service (interaction and problem resolution); and Incentive/Compensation/Price as well as shipping cost/landed price under Economic Efficiency (value perception).

The integration followed three operational principles: semantic consolidation, merging functionally aligned, semantically proximate constructs into a single higher-order dimension (e.g., Efficiency, System availability, and Website design into Ease of Use); context retention, retaining fresh-specific, experience-critical process factors (cold-chain integrity, delivery timeliness, package condition, tracking, and reverse logistics) as a distinct Logistics Service Quality dimension and allocating result-oriented factors (conformity to description, on-time arrival, freshness/intactness) to Fulfillment to reflect the process–outcome distinction; and de-duplication and reclassification, treating privacy/security/system availability as “in-use assurance” within Ease of Use rather than as standalone dimensions, classifying product quality in fresh contexts as a result attribute within Fulfillment, and handling purely presentational information/content quality as measurement items under Ease of Use or Fulfillment rather than as an independent dimension.

Table 2.2: Literature-to-Framework Dimension Mapping Matrix

Fresh E-commerce Dimension	Mapped Original Dimensions	Key References
Fulfillment	Reliability, Fulfillment, Reliability/Fulfillment, Product Quality	Santos (2003); Parasuraman et al. (2005); Lee & Lin (2005); Yen & Lu (2008); Ladhari (2010); Blut et al. (2015); Jiang et al. (2016); Rita et al. (2019); Kalia & Paul (2021); Lee et al. (2020); Lin (2020); Ma & Li (2020); Hou & Wang (2022); Zhu & Wang (2024)
Logistics Service Quality	Logistics, Logistics and Distribution, Packaging and Logistics	Lin (2020); Ma & Li (2020); Hou & Wang (2022)
Ease of Use	Efficiency, System Availability, Website Design, Ease of Use/Usability, Web Design, Convenience	Santos (2003); Parasuraman et al. (2005); Lee & Lin (2005); Yen & Lu (2008); Ladhari (2010); Blut et al. (2015); Jiang et al. (2016); Rita et al. (2019); Kalia & Paul (2021); Hou & Wang (2022); Zhu & Wang (2024)
Customer Service	Support, Communication, Contact, Responsiveness, Care, Customer Service, After-Sales Service, Customer Care	Santos (2003); Lee & Lin (2005); Yen & Lu (2008); Ladhari (2010); Blut et al. (2015); Jiang et al. (2016); Kalia & Paul (2021); Lin (2020); Ma & Li (2020); Hou & Wang (2022); Zhu & Wang (2024)
Economic Efficiency	Incentive, Compensation, Price, Economic Efficiency	Santos (2003); Kalia & Paul (2021); Ma & Li (2020); Lee et al. (2020)

This study departs from traditional models by reinterpreting their constructs for a digitally native and home delivery context. In such settings, tangibles lose salience and are effectively replaced by interface quality and system availability, while assurance is conveyed primarily through privacy, security, and system stability, treated here as safeguards within ease of use. Traditional reliability and responsiveness are disentangled into two analytically clearer facets: fulfillment, which evaluates whether outcomes meet promised standards, and customer service, which addresses responsiveness, communication quality, problem

resolution, and recovery. Moreover, the distinctive features of fresh ecommerce bring to the foreground two themes that are comparatively muted in classic frameworks, namely logistics process quality and economic efficiency. The former concerns the capability to deliver orders well through timely, stable, and temperature-controlled operations, and the latter captures judgments about price fairness, access to promotions, add-on costs, and overall affordability. The resulting framework with five dimensions does not reject SERVQUAL; rather, it rearticulates its core logic for the fresh ecommerce setting by preserving the substantive intent of reliability, responsiveness, and assurance while redrawing boundaries along process, outcome, and value so that the dimensions remain aligned with the literature and reflect the cues that guide consumer decisions in this category.

2.2.1.1 Fulfillment

Fulfillment refers to conformance between outcomes and promises, including order accuracy and completeness, on-time delivery, and the freshness, integrity, and description consistency of received items. In the electronic service quality literature, fulfillment is treated as a core pillar, and many studies position reliability and fulfillment as the foundational dimension of online service quality. In fresh product contexts, product quality, freshness, and physical integrity are best treated as fulfillment outcomes rather than as a separate construct (Parasuraman et al., 2005; Ladhari, 2010; Blut et al., 2015; Lee et al., 2020; Lin, 2020; Ma & Li, 2020). Conceptually, fulfillment is distinct from logistics, which concerns the process, whereas fulfillment evaluates whether the outcome meets the promised standard.

Ferreira et al. (2025) use structural equation modeling to show that confirmation of freshness significantly increases customer satisfaction, which in turn strengthens repurchase

intention in online fresh grocery contexts. Drawing on a sample of 1,562 e-commerce users, Akıl and Ungan (2022) report that order accuracy and the condition of items upon delivery (intactness) have significant positive effects on customer satisfaction. Using PLS-SEM on data from 719 quick commerce users, Al-Mu'ani et al. (2024) show that both order accuracy and delivery condition/intactness have significant positive effects on customer satisfaction, underscoring that receiving the right items in intact condition is a key driver of satisfaction.

2.2.1.2 Logistics Service Quality

Logistics service quality captures process performance such as delivery timeliness and stability, integrity of the cold chain and temperature control, package preservation, shipment tracking visibility, and reverse logistics for returns and exchanges. Given perishability and stringent temperature requirements, logistics and delivery form a distinct and salient evaluation dimension in fresh product markets, with prior research repeatedly showing significant effects on satisfaction and repurchase intention (Lin, 2020; Ma & Li, 2020; Hou & Wang, 2022). Separating logistics from fulfillment reduces conceptual overlap and aligns with customers' process and outcome evaluation path.

Harter et al. (2025) show that deviations from promised delivery times consistently affect interpurchase intervals, with late deliveries lengthening the next purchase gap and early deliveries shortening it. This connects process performance to future buying behavior. Hui et al. (2025) also document how logistics service quality impacts satisfaction in the cross-border e-commerce repurchase process and report positive effects of price fairness and customer satisfaction on repurchase intentions, emphasizing the importance of the process channel in digital grocery supply.

2.2.1.3 Ease of Use

Ease of use involves learnability, navigability, task completion efficiency, and in-use safeguards such as system availability, privacy, and security. Prior scales that emphasize efficiency and system availability, together with studies on website design and usability, converge on a unified usability construct; in mobile internet and mini program environments, privacy, security, and availability directly influence checkout and payment flows and are appropriately treated as safeguard subfacets within ease of use (Parasuraman et al., 2005; Lee & Lin, 2005; Ladhari, 2010; Blut et al., 2015; Jiang et al., 2016; Rita et al., 2019; Zhu & Wang, 2024). This dimension does not evaluate offline delivery or receipt outcomes and is distinct from value assessments about affordability, which are addressed under economic efficiency.

Nuralam et al. (2024) show in the Indonesian e-commerce market that perceived ease of use and perceived usefulness increase customer satisfaction and that satisfaction, in turn, increases repurchase intention, based on 300 valid responses analyzed with SEM. Imbayani et al. (2025) further find that the effect of perceived ease of use on repurchase intention operates through utilitarian value and customer experience in a mobile commerce setting, with significant indirect effects reported using PLS-SEM.

2.2.1.4 Customer Service

Customer service concerns the speed and effectiveness of responses, the quality of communication, problem resolution capability, and after sales care and compensation. Constructs such as support and communication, responsiveness and contact, and trust recur across general online settings, and fresh product studies explicitly highlight the importance of after sales care and compensation for remedying issues (Santos, 2003; Lee and Lin, 2005;

Yen and Lu, 2008; Ladhari, 2010; Blut et al., 2015; Lin, 2020; Ma and Li, 2020; Hou and Wang, 2022; Zhu and Wang, 2024). When disputes concern price fairness or whether a transaction is worthwhile, the evaluation belongs to economic efficiency; customer service focuses on explanation and recovery.

In e-commerce service-failure situations, higher-quality recovery policies boost consumers' sense of empowerment and satisfaction and are linked to greater repurchase intentions (Owusu et al., 2025). Return and after-sales services lower perceived uncertainty, which increases online shopping satisfaction and positively influences repurchase intention (Bukari et al., 2025). Across service-industry samples, the size of the service quality gap and recovery satisfaction significantly impact repurchase intention, with service recovery playing a moderating role (Tseng & Yong, 2025).

2.2.1.5 Economic Efficiency

Economic efficiency is the overall perception of price fairness and value for money, covering access to promotions, the reasonableness of add-on costs such as shipping and packaging, transparency of the final payable amount, and overall affordability. In online settings, incentives, compensation, and prices are not merely ancillary; they are perceived as a distinct quality facet. In the fresh category, which features high purchase frequency and strong sensitivity to shipping fees and promotions, economic efficiency is especially consequential for satisfaction and repurchase intention (Kalia & Paul, 2021; Lee & Cha, 2020; Ma & Li, 2020; Santos, 2003). This dimension is separate from ease of use and fulfillment and focuses on the alignment between value delivered and costs incurred.

Evidence from JD Fresh shows that across 34 product categories between July 1, 2023 and July 31, 2024 (Quan & Xiao, 2024), a cleaned sample of 24,907 reviews indicates

in multiple regressions that the price variable has a positive and significant effect on satisfaction; the price coefficient for new customers is about 0.0177 at the 0.1 percent level, while the coefficient for repeat customers is about 0.0085, indicating higher price sensitivity among newcomers. A structural model that integrates 1,252 online reviews and 509 valid questionnaires for a fresh platform's Aksu apples reports a positive path from perceived value to satisfaction with a coefficient of 0.414 (Ren et al., 2025), alongside significant positive effects of platform experience and perceived quality. Consistent with this pattern, an empirical study of 515 fresh e-commerce users shows that product price and service convenience raise satisfaction and that satisfaction transmits these effects to repurchase intention (Liu et al., 2023). Taken together, these results situate economic efficiency as a direct driver of satisfaction and an indirect driver of repurchase through satisfaction.

2.2.2 Customer Satisfaction

According to Kotler (2012), customer satisfaction is the emotional state of feeling content or disappointed that happens when customers compare the actual results of a product with what they expected. Customers are unhappy if the actual results are below expectations, satisfied if they meet expectations, and pleasantly surprised if they go beyond expectations. Achieving high customer satisfaction is vital in marketing because products with average performance risk being replaced when better options are available, while those that create high satisfaction build strong emotional bonds, making customers less likely to leave. This emotional connection helps ensure long-term loyalty and improves the company's profitability. The core of marketing is customer satisfaction, which drives repeat business.

The concept of customer satisfaction is rooted in the expectation-disconfirmation theory, which posits that satisfaction stems from the subjective comparison between a

customer's expectations of a product or service and their actual experience (Oh, 1999). Customers' assessment of satisfaction is influenced by both positive and negative emotions, as well as cognitive confirmation (Nisar & Prabhakar, 2017). Online shopping offers a different customer experience compared to traditional shopping, necessitating an adaptive approach to evaluating customer satisfaction in the online environment. A recent study by Wang (2023) revealed that e-satisfaction is closely linked to customers' evaluation of their previous online shopping experiences in relation to their expectations. In this study, e-satisfaction is defined as customers' subjective assessment of their online shopping experience within the online marketplace, based on their personal experiences and expectations.

In a complex and ever-changing market environment, fresh e-commerce platforms must learn how to satisfy customers to sustain their growth and market share. Managers need to recognize that mere customer satisfaction is insufficient for retaining customers. To cultivate loyalty, customers must be not just satisfied but delighted (Ladhari, 2008). Financial success and excellence are attributed to having satisfied customers. Customer satisfaction is crucial for establishing long-term customer relationships (Patterson, 1997). With the cost of acquiring new customers dropping due to internet-based sales, the more a company enhances customer satisfaction and retains existing customers, the better its chances of maintaining profitability in the long term.

Attracting new customers is a primary goal for marketing managers. However, in many instances, more emphasis is placed on retaining existing customers, as the cost of acquiring new ones can be up to five times higher than retaining current customers (Wu et al., 2021). Therefore, e-commerce providers should prioritize customer satisfaction to keep

their existing customers, since it positively influences consumer loyalty and word-of-mouth referrals (Akıl & Ungan, 2022).

2.2.3 Repurchase Intention

Repurchase intention signifies a consumer's willingness to make future purchases from an online store, where they are likely to revisit the store and potentially recommend it to others within their network (Kim et al., 2012). Research has shown that E-Service Quality positively influences e-satisfaction and also impacts consumer behavioral intentions, including revisiting the website, offering word-of-mouth recommendations, and engaging in repeat purchases. This influence can occur either directly or indirectly through e-satisfaction (Gounaris et al., 2010).

Customer behavioral intention variables are valuable indicators of customer satisfaction and the quality of business services. They include actions such as frequently revisiting the website, recommending the site to others, posting positive comments or reviews, and making repeat purchases (Liu et al., 2005). Mensah and Mensah (2018) found that service quality has a positive effect on repurchase intention. Studies, such as those by Chang et al. (2020); Kahn (2018), have demonstrated through examples that retailers succeed in retaining customers by providing an enjoyable and frictionless customer experience. Felix and Rembulan (2023) suggest that customer experience and satisfaction have a positive and significant impact on repurchase intention on online shopping sites. De Toni et al. (2018) assert that perceived value has a favorable impact on repurchase intent. Essentially, consumers who perceive higher value in a specific product or service are more likely to make repeat purchases (Retnowati & Mardikaningsih, 2021). Consumers' continued willingness to purchase from a fresh e-commerce company also reflects the

company's profitability potential and its ability to gain a sustained competitive advantage, which holds significant practical and economic value for the survival and growth of the company (Ou et al., 2014). Therefore, based on the results of previous studies, this study regards consumers' continued willingness to buy as an important outcome variable.

2.3 Underpinning Theories

Expectation-Confirmation Theory, Stimulus-Organism-Response Theory, and Means-Ends Chain Theory are commonly utilized theoretical frameworks in psychology, marketing, and behavioral research. This section presents a review of relevant research on these theories.

2.3.1 Expectation-Confirmation Theory

Expectation-Confirmation Theory (ECT) originated from consumer behavior research and was initially introduced by Richard L. Oliver in his seminal work on consumer satisfaction and expectation processes (Hossain & Quaddus, 2012). Oliver's research established the foundation for comprehending how consumer expectations, and their subsequent confirmation or disconfirmation, affect satisfaction and post-purchase behavior.

Expectation-Confirmation Theory (ECT) proposes a model comprising five dimensions: expectation, cognitive performance, confirmation, satisfaction, and repurchase intention. This theory suggests that consumers develop expectations prior to acquiring a product or service, and following product usage, they contrast their actual experience with these preconceived expectations. The result of this comparison shapes consumer satisfaction, which in turn influences their inclination to make repeat purchases or continue using the product.

The core structure of the theory is illustrated in Figure 2.1. As can be seen from the framing diagram of the Expectation-Confirmation Model, expectations and perceived performance influence the confirmation factor; confirmation and expectations jointly influence consumer satisfaction; and satisfaction ultimately influences consumers' willingness to repurchase.

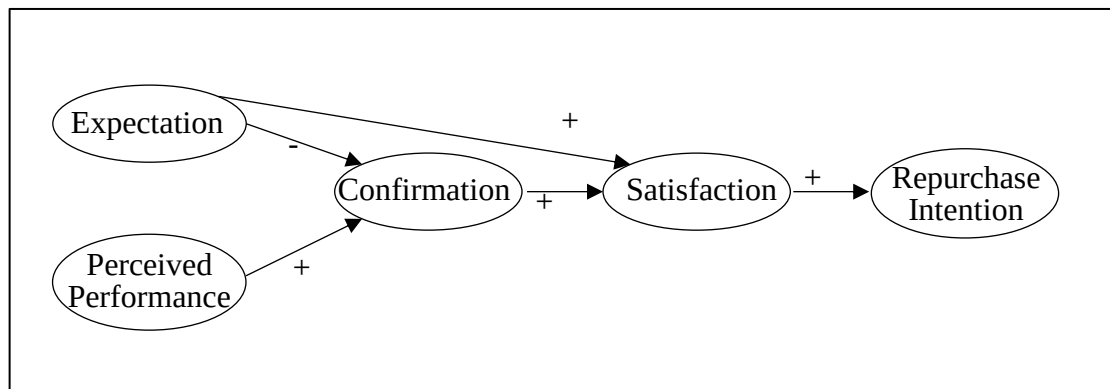


Figure 2.1: Expectation-Confirmation Theory (ECT) Model

Source: Understanding information systems continuance: An expectation-confirmation model (Bhattacharjee, 2001)

Expectation-Confirmation Theory (ECT) was broadly applied in consumer behavior research to explain how consumers form satisfaction and their subsequent purchase intentions following the purchase of products or services. Pradana (2022) examined the repeat purchase intention of e-commerce users from the perspective of service quality and Expectation-Confirmation Theory. Ashfaq et al. (2019) investigated the relationship between customer expectations, perceived enjoyment, perceived ease of use, satisfaction, and repurchase intention for online second-hand products using the Expectation-Confirmation Model. Yi et al. (2024) utilized the Expectation-Confirmation Theory (ECT) as a research framework to analyze the process by which satisfaction and subsequent purchase intention are formed among live streaming shopping (LSS) consumers after they purchase products or services.

ECT provides the causal core whereby perceived performance, operationalized as Fresh E-commerce Service Quality, influences Customer Satisfaction, which in turn drives Repurchase Intention (Bhattacharjee, 2001; Oliver, 1980), with a plausible direct quality→repurchase path retained. Other lenses are used as supporting theories to specify the construct domain and modeling choices.

2.3.2 Stimulus-Organism-Response Theory

Stimulus-Organism-Response Theory (S-O-R) was developed from the behaviorist theory of S-R, first proposed by Woodworth (1929), and is rooted in environmental psychology. This theory argues that environmental stimuli elicit an organism's intrinsic experience, which subsequently leads to an individual's intrinsic or extrinsic responses. Intrinsic responses include attitudes, satisfaction, and the like, while extrinsic responses involve proactive or avoidance behaviors. The S-O-R framework highlights the importance of cognitive and affective processes in an individual's response to external stimuli. Here, Stimulus (S) is the influencing factor, Organism (O) represents the individual's mental state, and Response (R) is the resulting reaction.

Stimulus (S) serves as the initiating factor, comprising external factors that lead to changes in an individual's internal state (Hsiao & Tang, 2021). Stimuli can be classified into two categories: the external environment and the external context. The external environment refers to objectively existing stimuli, such as the shopping environment, shopping atmosphere, and corporate work environment. In contrast, the external context primarily pertains to stimuli that are perceived by the individual, including social interaction support, reliability, content quality, etc.

The organism (O) serves as a mediating variable, acting as a repository for an individual's affective and cognitive systems, which encompass mood, emotions, experiences, and beliefs. The individual's emotional response to the environment can be seen as an internal state that is manifested through affective and cognitive states. The affective state refers to an individual's emotional reaction to the environment, including temperament (Petrie, 1967), such as joy, happiness, surprise, or love, and is triggered by a stimulus (Kamboj et al., 2018).

Response (R) is the outcome variable, referring to the final decision made by the individual in response to a stimulus. Cognitive response specifically pertains to the cognitive processes that an individual undergoes during interaction with a stimulus. It represents "the individual's final reaction to a particular stimulus and internal state" (Hsiao & Tang, 2021) and categorizes behaviors into approach and avoidance, including satisfaction or dissatisfaction with the surrounding environment (Robert & John, 1982).

The S-O-R framework is illustrated in Figure 2.2. The S-O-R model has been extensively utilized in research within the field of services. With the advent of online shopping, the S-O-R theory has gained widespread application in studying consumer behavior in both online platform usage scenarios and online shopping contexts.

The S-O-R framework holds a prominent position among numerous global management theories and, consequently, has been extensively developed and widely utilized across diverse research fields. Le et al. (2022), utilizing the S-O-R framework, examined the elements that affect consumers' impulsive buying behavior while shopping online. The study revealed that shopping motivation factors and marketing activities serve as the initial input stimuli (Stimuli), while hedonic shopping value functions as the organism (O), ultimately

leading to the desire and behavior of impulsive purchasing (Response). Tuncer (2021) applied the S-O-R framework to examine the relationships among IT affordance, immersive experience, trust, and social commerce intentions. The study showed that IT affordance, acting as the Stimulus, influences users' immersive experience and trust (Organism), which in turn impacts their social commerce intentions (Response).

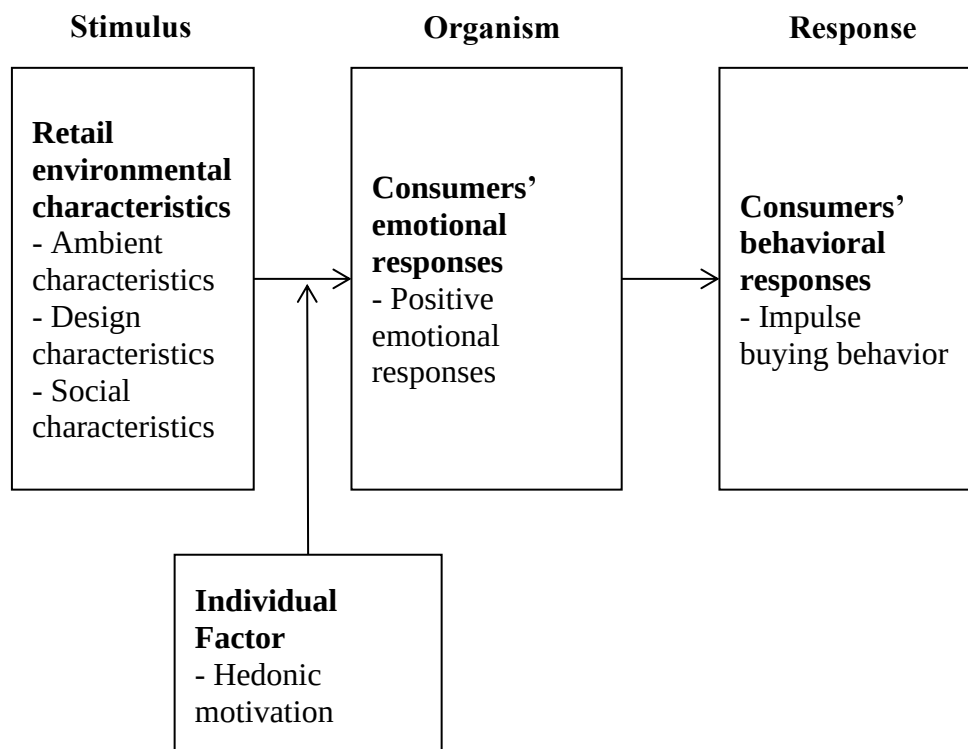


Figure 2.2: Stimulus-Organism-Response Theory (S-O-R) Model

Source: Application of the Stimulus-Organism-Response model to the retail environment: the role of hedonic motivation in impulse buying behavior (Chang et al., 2011)

The Stimulus–Organism–Response (S–O–R) framework is adopted to explain how service quality shapes customer behavior. Five fresh e-commerce service-quality dimensions operate as external stimuli; Customer Satisfaction represents the organism; Repurchase Intention constitutes the response (Eroglu et al., 2001; Mehrabian & Russell, 1974). This logic supports a directional pathway, Dimensions → Fresh E-commerce Service Quality →

Customer Satisfaction → Repurchase Intention, while allowing both an aggregate-quality route and component-level effects.

2.3.3 Means-Ends Chain Theory

The Means-Ends Chain Theory, developed by Olson and Reynolds, is presented in their book “Understanding Consumer Decision Making: The Ultimate Approach to Marketing and Advertising Strategy” (Reynolds & Olson, 2001). Since then, the MEC has been extensively validated through empirical research and has found application in a diverse range of fields, including advertising, brand equity analysis, consumer engagement, and consumer behavior (Borgardt, 2018).

The Means-Ends Chain theory is a methodological framework utilized to uncover the connections between product attributes, the subsequent outcomes for consumers, and the personal values that these outcomes reinforce (Reynolds & Gutman, 2001). Means pertain to objects (like products) or activities (such as running or reading) in which individuals partake. Conversely, ends embody desirable states of being, such as happiness, security, and achievement.

Means-ends chain is a framework designed to clarify how the choice of a product or service contributes to attaining a desired outcome. The MEC sequentially links product attributes (A) to the outcomes of product use (C) and personal values (V) (Veludo-de-Oliveira et al., 2006). Attributes refer to the features or facets of a product or service. Consuming products or services leads to consequences (both functional and psychosocial) for individuals (Chiu, 2005). Functional consequences are the immediate results stemming from the use of consumer products. Conversely, psychosocial consequences relate to the

personal and social effects that arise from product use. Figure 2.3 illustrates the structure of the MEC.

Means-Ends Chain Theory is often utilized to comprehend how consumers fulfill their personal values or ultimate goals (Ends) through the attributes (Means) of products or services. Xu et al. (2021) applied the Means-Ends Chain Theory to examine the consumer value pathways in cross-border e-commerce, constructing an Attribute-Consequence-Value (A-C-V) pathway map for the consumer purchase process. Nguyen et al. (2021) employed the Means-End Chain Theory to explore the underlying consumer motivations for virtual supermarket shopping.

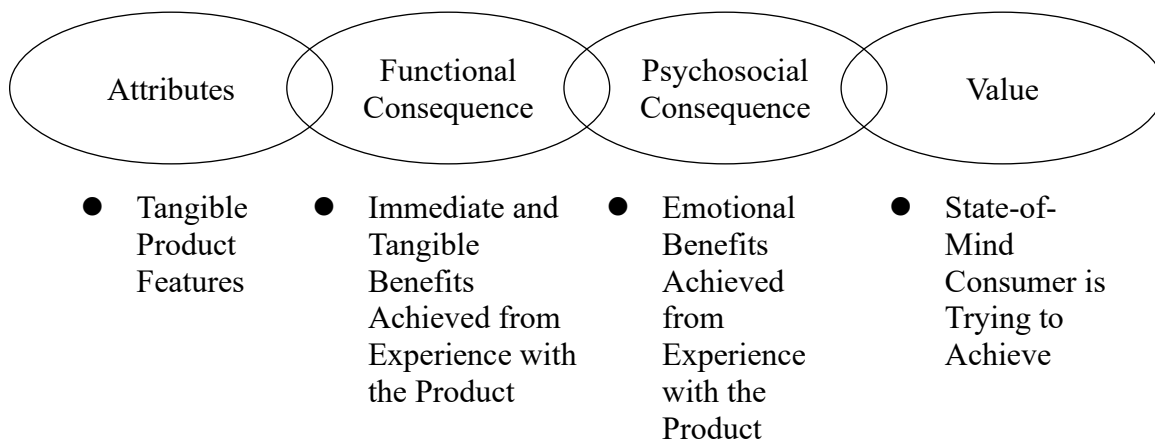


Figure 2.3: Means-End Approach (MEC) Framework

Source: Understanding consumer decision making: The means-end approach to marketing and advertising strategy(Reynolds & Olson, 2001)

The Means-End Chain Theory provides a structure for examining how consumers connect particular product or service characteristics to their individual needs, objectives, and beliefs. In the study of service quality in fresh e-commerce, this theory aids in revealing why customers exhibit particular preferences and satisfaction with certain aspects of service quality, and how these preferences and satisfaction influence their shopping decisions and willingness to repurchase. The Means-End Chain Theory offers a theoretical basis for

delving deeper into the aspects of service quality in China's fresh e-commerce and their connection to customer satisfaction and repeat purchase intentions.

2.4 Conceptual Framework

Research on service quality is rooted in the expectation–confirmation tradition. Two foundational streams dominate. The Nordic school distinguishes technical quality (what is delivered) from functional quality (how it is delivered), with corporate image as a moderator (Grönroos, 1984). The American school operationalizes quality as the expectation–perception gap, culminating in SERVQUAL with five dimensions—reliability, responsiveness, assurance, empathy, and tangibles, widely applied across offline settings (Parasuraman et al., 1988; Parasuraman et al., 1985). Satisfaction formation within this logic is formalized in Oliver (1980).

As commerce migrated online, e-service quality instruments were introduced to capture the joint role of front-end interfaces and back-end processes. Representative scales include SITEQUAL (ease of use, design, processing speed, security) (Yoo & Donthu, 2001), WebQual (information, interaction, usability) (Loiacono et al., 2007), eTailQ (website design, reliability, privacy/security, customer service) (Wolfenbarger & Gilly, 2003), and E-S-QUAL/E-RecS-QUAL (efficiency, system availability, fulfillment, privacy; and recovery facets such as responsiveness, compensation, contact) (Parasuraman et al., 2005; Zeithaml et al., 2002). Reviews and meta-analyses converge on several stable clusters across instruments: a usability/availability cluster (efficiency, system availability, website design), a fulfillment/reliability cluster (accuracy, completeness, on-time delivery, promise keeping), a customer service/recovery cluster (responsiveness, problem resolution, contact), and a security/privacy cluster (Blut et al., 2015; Fassnacht & Koese, 2006; Ladhari, 2010b).

Fresh e-commerce features perishability, time sensitivity, and cold-chain dependence, which elevate attention to both the delivery process and the delivered outcome. Recent studies in fresh/grocery settings consistently show that customers evaluate service quality through process cues such as logistics timeliness, temperature control/packaging integrity, shipment visibility, and reverse logistics, alongside outcome cues such as conformity to description and freshness/intactness on arrival, and a distinct value lens captured by economic efficiency (Lee et al., 2020; Lin, 2020; Ma & Li, 2020; Wang, 2021; Hou & Wang, 2022; Zhu & Wang, 2024). Synthesizing these insights with established online clusters, e-service quality in this context is organized into five higher-order dimensions: Fulfillment, conformity to description/promise, encompassing accuracy, completeness, on-time arrival, and delivered product condition/freshness/intactness (Lin, 2020; Ma & Li, 2020; Zhu & Wang, 2024); Logistics Service Quality, delivery timeliness and stability, cold-chain/temperature control, package integrity, shipment tracking/visibility, and reverse-logistics experience (Lin, 2020; Ma & Li, 2020; Hou & Wang, 2022); Ease of Use, learnability, navigability, and task efficiency together with in-use assurance (system availability, privacy, security) that enables smooth end-to-end transactions (Wang, 2021; Zhu & Wang, 2024); Customer Service, responsiveness, clarity of communication, problem resolution, and after-sales care/compensation (Lin, 2020; Ma & Li, 2020; Hou & Wang, 2022); Economic Efficiency, value perception including price fairness/value-for-money, attainability/credibility of promotions, ancillary costs (shipping/packaging), and landed-price transparency (Lee et al., 2020; Ma & Li, 2020; Zhu & Wang, 2024).

Conceptual boundaries are specified to prevent redundancy and align with consumer cognition in this category: process (logistics) is separated from outcome (fulfillment); in-use assurance (privacy/security/availability) is embedded within ease of use rather than treated

as a standalone dimension; product quality at receipt is treated as a fulfillment outcome attribute; the fairness/credibility of monetary remedies and price components are evaluated within economic efficiency, whereas the timeliness and clarity of handling issues are evaluated within customer service (Lee et al., 2020; Lin, 2020; Hou & Wang, 2022; Zhu & Wang, 2024).

Service quality attributes in online retail, including fresh e-commerce, significantly influence customer satisfaction and, consequently, repurchase intention. In fresh e-commerce logistics, delivery timeliness, reliability, and shipment visibility enhance satisfaction and trust, which then drive repurchase intention (S. Chen et al., 2023; Hong et al., 2019; Jiang et al., 2021). In online fresh grocery shopping, product condition upon receipt, customer support quality, and packaging integrity directly improves satisfaction and lead to stronger repurchase intention (Lin et al., 2021). Broader e-service quality research shows that, while service quality may not always have a direct effect on repurchase intention, it consistently boosts trust and satisfaction, which mediate the effect on repurchase behavior (Akmal & Thamrin, 2025; Iffan et al., 2024; Nafisah & Istanti, 2025). In online grocery contexts, ease of use, perceived control, and positive attitudes significantly increase satisfaction, which then encourages repurchase intention (Vazirani, 2022).

Figure 2.4 displays the proposed conceptual framework that combines the S–O–R structure with ECT and MEC perspectives. Five service quality dimensions, Fulfillment, Logistics Service Quality, Ease of Use, Customer Service, and Economic Efficiency, serve as Stimuli (S) that influence the Organism state (O: Customer Satisfaction) and the Response (R: Repurchase Intent). Each dimension is hypothesized to improve Customer Satisfaction (H1–H5) and directly impact Repurchase Intent (H6–H10). It is expected that Customer

Satisfaction positively affects Repurchase Intent (H11) and partially mediates the effects of each service quality dimension on Repurchase Intent (H12a–H12e).

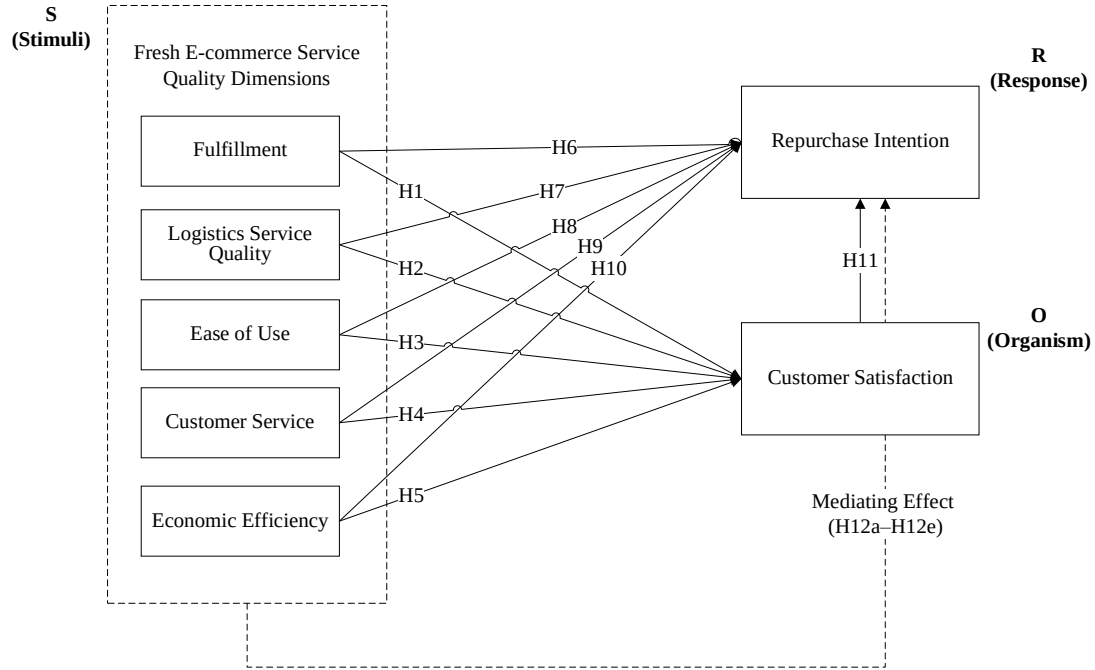


Figure 2.4: Research Framework

Note: The model adopts a Stimulus–Organism–Response (S–O–R) structure, in which the five service quality dimensions serve as the Stimuli (S), customer satisfaction represents the Organism state (O), and repurchase intention constitutes the Response (R). In line with Expectation–Confirmation Theory (ECT), each dimension contributes to the confirmation of customer expectations, thereby enhancing satisfaction. From a Means–End Chain (MEC) perspective, these service attributes act as means to achieve functional or value-based consequences.

2.5 Hypothesis Development

Drawing on prior theories and empirical studies, this section develops hypotheses about the relationships between dimensions of fresh e-commerce service quality and two outcomes, customer satisfaction and repurchase intention, in the context of China’s fresh e-commerce.

2.5.1 Investigate which service quality dimensions positively impact consumer satisfaction

Researchers widely agree on the positive impact of E-Service Quality on customer satisfaction (Suhaily, 2017). Recent research has revealed a positive correlation between e-service quality and customer satisfaction, as well as an increase in repurchase intentions (Patwardhan, 2021). When it comes to online clothing purchases, researchers have discovered that website reputation and E-Service Quality in e-tailing are significant predictors of customer satisfaction (Bobalca et al., 2021). By examining the influencing factors, the study revealed that customer satisfaction has a notable positive effect on both customer loyalty and customers' perceived quality (Shaoling, 2016).

Companies must appropriately adjust the fundamental components of consumer satisfaction to conduct customer satisfaction assessments more effectively. This evaluation process is essential for gaining a deeper understanding of customers, thereby enabling better management decisions (Woodside et al., 1989). Customer satisfaction serves as the primary basis for assessing the quality of products and services that a firm offers to its customers (Brady, 2000). Suppose an enterprise can establish an objective and reasonable satisfaction evaluation system. In that case, it can not only thoroughly analyze its development situation but also contribute to the healthy growth of the enterprise. The critical aspect of customer satisfaction lies in identifying the attributes that customers consider significant in meeting their needs and expectations (Yang et al., 2011).

To develop the hypotheses, this study draws on established service and electronic service quality research, the expectation–confirmation tradition of satisfaction formation, and behavioral models of online consumption (Oliver, 2010; Parasuraman et al., 2005). Prior work shows that perceived performance on core service attributes shapes satisfaction and

downstream intentions, and that these effects can be traced to reliability in delivery, interface usability, responsive support, and value perceptions (Bhattacharjee, 2001; Brady & Cronin, 2001).

Fulfillment represents the outcome quality of e-commerce and maps directly to consumers' judgments of whether realized performance meets or exceeds prior expectations. Along the expectation confirmation sequence, accurate order picking, freshness, and intact condition upon arrival strengthen confirmation and thereby raise satisfaction. In a fresh grocery context marked by high time sensitivity and product risk, strong fulfillment also lowers uncertainty and perceived risk, reinforces trust in the platform and positive affect, and ultimately translates into higher customer satisfaction. Large-scale review analytics and hybrid modeling report significant positive effects of product quality on satisfaction in fresh categories (Guan et al., 2022). Customer experience research in online grocery also finds that delivery experience improve attitudes and later intentions (Anshu et al., 2022).

H1: Fresh e-commerce fulfillment has a significant positive effect on customer satisfaction.

Logistics service quality, including delivery speed, dependable time windows, cold chain integrity, and protective packaging, reduces uncertainty and perceived risk, which increases satisfaction. Recent empirical work develops and validates a logistics service quality scale for fresh e-commerce and shows a positive association with satisfaction (Wang et al., 2024). Studies on sustainable fresh food logistics likewise identify timeliness and packaging integrity as significant drivers of satisfaction (Jiang et al., 2021).

H2: Fresh e-commerce Logistics Service Quality has a significant positive effect on customer satisfaction.

When interfaces are clear and tasks are straightforward, cognitive effort decreases and shopping becomes more seamless, which boosts satisfaction. Evidence from structural equation modeling indicates that website design and usability enhance the online shopping experience and satisfaction (Guo et al., 2023; Karani et al., 2021), and meta-analytic structural models in digital commerce show a positive link from perceived ease of use to satisfaction and continued use (Mishra et al., 2023).

H3: Fresh e-commerce ease of use has a significant positive effect on customer satisfaction.

Responsive, transparent, and fair customer service restores confidence when problems occur and strengthens satisfaction. Recent reviews of electronic service failure and recovery show that timely responses and procedural fairness increase satisfaction and reduce defection intentions (Foroudi et al., 2025), while evidence in electronic retail highlights the role of swift and candid remedies after delivery or fulfillment issues.

H4: Fresh e-commerce customer service has a significant positive effect on customer satisfaction.

Perceived economic efficiency, understood as price fairness and value for money, consistently predicts satisfaction. A recent comprehensive meta-analysis confirms robust positive effects of perceived value on satisfaction and outcomes related to repurchase across service settings (Blut et al., 2024), and studies in online food and delivery contexts show that fair pricing and favorable cost benefit tradeoffs raise satisfaction through perceived value (Konuk, 2019; Phan & Le, 2023).

H5: Fresh e-commerce economic efficiency has a significant positive impact on customer satisfaction.

2.5.2 Analyze which service quality dimensions positively impact consumer repurchase intention

Wilson et al. (2019) found that service quality has a positive effect on e-commerce consumers repurchase intention in Asia, Australia, and Europe. In the online shopping context of Indonesian marketplaces, Rachbini et al. (2021) discovered that e-service quality positively impacts customer satisfaction, and both e-service quality and customer satisfaction positively influence consumers' repurchase intention.

Defined as order accuracy and product condition upon arrival, fulfillment operates as a concrete outcome cue that immediately reassures buyers that what they received matches what they ordered. This reduces perceived loss and corrective effort and directly strengthens the intention to buy again. Evidence in fresh e-commerce shows that “product-in-hand” quality, including accuracy and intactness, is a primary driver of repurchase intention (Ma et al., 2022). Research in rapid delivery settings likewise reports that order accuracy and shipment condition are among the strongest logistics levers linked directly to loyalty and repeat patronage, capturing a direct fulfillment → repurchase path (Al-Mu'ani et al., 2024). Last-mile work in online retail further shows that delivery quality and the condition of received goods are directly associated with repeat behavior (Aljohani, 2024).

H6: Fresh e-commerce fulfillment has a significant positive effect on customers repurchase intention.

Key Logistics Service Quality (LSQ) facets such as timeliness, tracking transparency, cold-chain integrity and condition, reverse-logistics convenience, and delivery

professionalism provide immediate instrumental benefits that make customers more willing to reorder, even without invoking attitudinal mediators. Empirical studies find that electronic or logistics service quality directly predicts repurchase intention (Jain et al., 2021) and that higher LSQ increases repurchase intention across cross-border contexts (Do et al., 2023). Evidence across logistics services also documents a positive LSQ, reuse link at the intention level (Lin et al., 2023).

H7: Fresh e-commerce Logistics Service Quality has a significant positive effect on customers repurchase intention.

Ease of use lowers effort in search, configuration, and checkout, offering direct utility gains that translate straight into willingness to repeat purchase. Meta-analytic evidence on online grocery shows that technology evaluations tied to ease and fluency are positively related to purchase and repurchase intentions (Tyrväinen & Karjaluo, 2022). Multi-market evidence further indicates that perceived ease of use exerts a direct positive effect on repurchase intention in e-commerce (Cuong, 2023).

H8: Fresh e-commerce ease of use has a significant positive effect on customers repurchase intention.

Effective problem handling, including responsiveness, clear explanations, and fair compensation, creates an immediate sense of resolution and restores buyers' readiness to order again, yielding a direct positive effect on repurchase intention. Studies show that successful complaint handling predicts higher repurchase intentions in social and online retail settings (Istanbulluoglu & Sakman, 2024; Owusu et al., 2025).

H9: Fresh e-commerce customer service has a significant positive effect on customers repurchase intention.

Fair, stable, and transparently economical offers, including sensible delivery-fee thresholds, bundling or savings, and membership value, directly increase the perceived payoff of returning to the platform, thereby lifting repurchase intention. A comprehensive synthesis shows customer perceived value has a substantive positive association with repurchase intentions (Blut et al., 2024), and in e-commerce settings price fairness together with service quality has a direct positive effect on repurchase intention (Do et al., 2023).

H10: Fresh e-commerce economic efficiency has a significant positive impact on customers repurchase intention.

2.5.3 Assess the impact of consumer satisfaction on consumer repurchase intention

Despite the widespread establishment of a positive correlation between customer satisfaction and repurchase intention in existing research, a deeper exploration of this relationship within the unique context of China's fresh e-commerce is still essential. It is noteworthy that in the real-world operations of this industry, the so-called "satisfaction paradox" (Du, 2023) frequently occurs, where some highly satisfied customers do not become loyal repeat buyers as expected. This anomaly not only contradicts the expectations of traditional theories but also highlights the complex nature of the relationship between customer satisfaction and repurchase intention in this industry. Therefore, this study proposes the following hypothesis:

H11: Fresh e-commerce customer satisfaction has a significant positive effect on customer repurchase intention.

2.5.4 Effect of E-service Quality on Repurchase Intention through Customer Satisfaction

When examining the relationship between e-service quality and e-repurchase intention, numerous studies have shown that e-service quality does not directly influence e-repurchase intention but rather affects it indirectly by improving e-satisfaction (Purnamasari & Suryandari, 2023). The quality of e-services can indirectly impact and increase the repurchase intention of e-commerce customers through customer satisfaction. A quantitative study, which involved distributing questionnaires to 344 e-commerce consumers of Shopee, Tokopedia, Lazada, and Bukalapak across Indonesia, confirmed the mediating role of satisfaction (Ginting et al., 2023). For consumers using the e-commerce platform Shopee.com, the connection between e-service quality and online repurchase intention is significantly mediated by e-satisfaction (Fanani, 2020).

For fulfillment, order accuracy and received condition are closely linked to customer satisfaction and future behavioral intentions. In quick commerce, shipment condition and order accuracy significantly boost customer satisfaction, with order accuracy having the most significant impact (Al-Mu'ani et al., 2024). In fresh-food online shopping, the product in hand and packaging improves repurchase intention by increasing satisfaction (Ma et al., 2022). Additionally, in a large e-retail sample, factors like timeliness, order condition, order accuracy, and discrepancy handling enhance satisfaction, which in turn supports loyalty and repeat purchases (Akıl & Ungan, 2022). These findings offer a satisfaction-based foundation for connecting fulfillment to repurchase.

For logistics service quality, delivery timeliness and stability, information visibility, and returns handling consistently improve customer satisfaction and increase repurchase rates. In fresh e-commerce, logistics service quality has a proven positive connection to

customer satisfaction (Yang et al., 2024). In cross-border settings, factors like delivery service quality, delivery stability, information delivery, and return logistics, often combined with price fairness, predict repurchase intention through satisfaction, confirming a satisfaction-mediated pathway from process performance to repeat purchases (Hui et al., 2025).

For clarity, structural models show that perceived ease of use and perceived usefulness boost customer satisfaction, which then increases repurchase intention; additional evidence also reports a positive, satisfaction-driven pathway from usability perceptions to repeat purchases on e-commerce platforms (Imbayani et al., 2025; Nuralam et al., 2024).

Stronger service-recovery policies improve post-failure evaluations and are linked to higher repurchase intentions, aligning with a mechanism where recovery quality boosts satisfaction that then influences repurchase (Owusu et al., 2025).

For economic efficiency, evaluations of price fairness and value for money primarily support repurchase through satisfaction: in e-retail and cross-border e-commerce, the effects of timeliness and price fairness are partially or mediated mainly by satisfaction and loyalty as pathways to repeat purchase (Do et al., 2023; Hui et al., 2025).

This suggests that e-satisfaction, acting as a mediator, effectively conveys the positive effect of e-service quality on e-repurchase intention. In other words, enhancing e-service quality can boost customers' e-satisfaction, which in turn increases their e-repurchase intention. Based on these findings, the research hypotheses are presented as follows:

H12a: Customer satisfaction mediates the relationship between fulfillment and repurchase intention (positive indirect effect).

H12b: Customer satisfaction mediates the relationship between logistics service quality and repurchase intention (positive indirect effect).

H12c: Customer satisfaction mediates the relationship between ease of use and repurchase intention (positive indirect effect).

H12d: Customer satisfaction mediates the relationship between customer service and repurchase intention (positive indirect effect).

H12e: Customer satisfaction mediates the relationship between economic efficiency and repurchase intention (positive indirect effect).

2.6 Summary

This chapter provides a comprehensive review of the literature related to e-service quality, customer satisfaction, and repurchase intention within the context of China's fresh e-commerce. It explores key concepts such as the dimensions of e-service quality (including fulfillment, Logistics Service Quality, ease of use, customer service, and economic efficiency), customer satisfaction as an emotional state influenced by expectation-confirmation dynamics, and repurchase intention as a behavioral outcome. The chapter integrates theoretical frameworks, such as the Expectation-Confirmation Theory, Stimulus-Organism-Response Theory, and Means-Ends Chain Theory, to clarify the relationships among these constructs. Based on the insights from the literature, research hypotheses are formulated to investigate the impact of e-service quality dimensions on customer satisfaction and repurchase intention, with a particular focus on the mediating role of customer

satisfaction. This review lays the theoretical groundwork for the subsequent methodology chapter, which will outline the research design and methods used to test these hypotheses.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

The study adopts a pragmatic paradigm with an abductive approach to inquiry. Ontologically, it assumes a modest realist perspective: digital traces in customer reviews reflect multiple, context-dependent realities of service experience but are stable enough to be modeled as measurable constructs (Archak et al., 2011; Büschken & Allenby, 2016; Grimmer & Stewart, 2013). Epistemologically, knowledge is developed through empirical patterns identified in large-scale text data and verified by confirmatory statistical modeling (Blei et al., 2010); inference occurs iteratively between inductive discovery and deductive testing (Gelman & Shalizi, 2013). Axiologically, the study aims for value neutrality by using transparent, replicable procedures and reporting robustness checks (Creswell & Clark, 2017; Tashakkori & Teddlie, 2010).

Methodologically, the study employs a sequential, mixed-methods approach, moving from a qualitative phase to a quantitative phase, tailored to the context of fresh e-commerce. First, a machine-assisted qualitative phase applies topic modeling to identify potential service-quality dimensions from customer reviews inductively, followed by close reading to refine construct meanings and boundaries (Bai et al., 2021; Chauhan & Shah, 2021; Röder et al., 2015). Second, aspect-based sentiment analysis quantifies evaluative tone for each identified dimension at the review and sentence levels (Davoodi et al., 2025; Zhu et al., 2022), then aggregates these signals to product level (Peng et al., 2022). Third, a confirmatory quantitative phase uses covariance-based structural equation modeling to test hypothesized relationships among service quality dimensions, customer satisfaction, and

repurchase intention, including indirect effects through mediation (Kline, 2023b; Sarstedt, 2019).

The unit of analysis is the platform-by-product review record. These records are aggregated to form latent variables representing Fulfillment, Logistics Service Quality, Ease of Use, Customer Service, Economic Efficiency, Customer Satisfaction, and Repurchase Intention. The study uses a cross-sectional design, with data collected from August 2023 to August 2024. Sampling follows a purposive, theory-driven strategy that covers four main business models in China's fresh e-commerce: comprehensive e-commerce, front warehouse, store-warehouse integration, and community group purchase, in order to capture heterogeneity in logistics processes and service encounters (Liu & Hu, 2023). The dataset consists of publicly available post-purchase reviews gathered with compliant tools and Python routines.

To ensure credibility, the study assesses topic stability and semantic coherence by comparing alternative topic modeling parameterizations and using established coherence measures (Röder et al., 2015); validates sentiment classification with a manually labeled subsample, reporting accuracy, precision, and recall (Nair et al., 2024; Van Atteveldt et al., 2021; Zhu et al., 2022); evaluates measurement quality in structural equation modeling through internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (average variance extracted), and discriminant validity using the heterotrait to monotrait ratio of correlations and the Fornell and Larcker criterion (Fornell & Larcker, 1981; Henseler et al., 2015; Mardia et al., 2024); and examines overall model fit using multiple indices with recommended cutoffs and tests indirect effects with nonparametric bootstrapping (Cole & Preacher, 2014; Kline, 2023b; Yuan & Bentler, 2006).

Sensitivity analyses, including alternative aggregation rules and the exclusion of low information reviews, are reported to demonstrate robustness.

Only publicly available reviews are used, and personal identifiers are removed during processing. Data collection complies with platform terms of use, and results are reported in aggregate to prevent re-identification, aligning with current internet-mediated research ethics guidelines (Heise et al., 2019).

Section 3.2 explains data sources and collection methods. Section 3.3 details text processing, topic modeling, and sentiment procedures. Section 3.4 describes the structural equation modeling specification, estimation, and evaluation criteria.

3.2 Data Source

Reviews were collected from publicly available, post-purchase comments between August 2023 and August 2024 across four representative fresh e-commerce platforms in China: JD Fresh (integrated/traditional), Dingdong MaiCai (front-warehouse), Yonghui Superstores (store-warehouse integration), and Taocaicai (community group purchase). The sampling frame covered four product categories—fruits, vegetables, meat & eggs, and aquatic products. Within each platform $\times$ category, best-selling products were selected, and all reviews posted for those products during the window were retrieved.

3.2.1 Data Collection

Currently, China's fresh e-commerce industry is characterized by the coexistence of multiple business models. Among these, traditional e-commerce platforms (such as JD Fresh, Tmall Fresh), front-store warehouses (such as Dingdong Maicai, Daily Youxian, Meituan Maicai, etc.), and store-warehouse integrations (such as Yonghui Supermarket, Hema Fresh,

RT-Mart Youxian, etc.) are primarily established in first- and second-tier cities. Meanwhile, community group buying models (such as Taocaicai, Duoduo Maicai, Xingsheng Youxuan, etc.) mainly cater to the needs of users in the sinking market. As illustrated in Table 1.2, fresh e-commerce with different business models satisfies the consumption needs of consumers at various levels. Therefore, there is no dominant model in fresh e-commerce at present, and the coexistence of multiple business models is expected to continue (Wang & Xu, 2022). The aforementioned fresh e-commerce companies have secured a favorable competitive position with their respective advantages and are poised to continue expanding their market share in the future development of the industry.

To comprehensively observe fresh e-commerce in China, the data in this study is sourced from JD Fresh (traditional fresh e-commerce integration model), Dingdong MaiCai (front warehouse model), Yonghui Superstores (store-warehouse integration model), and Taocaicai (community group purchase model).

The selection of these four platforms as data sources is based on their representativeness of the diverse business models within China's fresh e-commerce industry, each catering to different consumer segments and market needs.

JD Fresh represents the traditional e-commerce model, leveraging JD.com's extensive logistics and supply chain infrastructure. This model suits consumers seeking a wide variety of fresh products with reliable delivery services, particularly in first- and second-tier cities where consumers have higher expectations for product quality and delivery speed.

Dingdong MaiCai exemplifies the front warehouse model, which emphasizes rapid delivery by establishing local warehouses nearer to consumers. This model is tailored to

urban consumers who prioritize convenience and quick access to fresh produce. It has gained significant popularity in major cities by offering fast delivery times and a user-friendly app experience.

Yonghui Superstores represent the store-warehouse integration model. This model merges the benefits of physical stores and online platforms, enabling consumers to shop both in-store and online. It appeals to consumers who value the option to choose between immediate in-store purchases and convenient home delivery. This model is especially effective in urban areas where foot traffic and online orders can be balanced.

Taocaicai stands as a prominent example of the community group purchase model, targeting consumers in the “sinking market” (third- and fourth-tier cities and rural areas). This model utilizes community-based purchasing groups to consolidate demand and offer competitive pricing on fresh products. It is particularly effective in reaching consumers who value affordability and social shopping experiences.

These four platforms collectively embody the coexistence of multiple business models within China’s fresh e-commerce industry, each possessing its own strengths and market positioning. By gathering data from JD Fresh, Dingdong MaiCai, Yonghui Superstores, and Taocaicai, this study intends to present a comprehensive view of the industry, capturing the varied consumer behaviors and market dynamics across different regions and consumer segments.

To ensure comprehensiveness and representativeness, the study focuses on four major fresh-produce categories: fruits, vegetables, meat & eggs, and aquatic products, because these categories account for a large share of consumer demand and market turnover. Reviews were collected from August 2023 to August 2024 across four representative

platforms in China: JD Fresh (integrated/traditional), Dingdong MaiCai (front-warehouse), Yonghui Superstores (store-warehouse integration), and Taocaicai (community group purchase). Sampling is stratified by platform $\times$ category. Within each stratum, best-selling products are selected using platform sales or “hot list” rankings. Mirror listings and duplicate SKUs are merged into a single product entry, and the next candidate replaces products lacking sufficient review text for analysis within the same stratum. For each selected product, all publicly available post-purchase reviews within the time window are retrieved, including both positive and negative feedback, to ensure the dataset reflects the full range of customer experiences and current market dynamics.

In total, the study amassed 77,183 reviews across the selected products. This extensive dataset serves as a robust foundation for statistical analysis and hypothesis testing, ensuring the findings are resilient and dependable. The data collection period was deliberately set from August, 2023, to August, 2024, to reflect a full year of market activity. This one-year timeframe is crucial as it captures seasonal fluctuations in consumer demand, product availability, and market trends, providing a comprehensive overview of the fresh produce market over a complete cycle.

Customer reviews on JD Fresh are accessible through its website. Octopus Collector (www.bazhuayu.com), also known as Bazhuayu Collector, is a powerful and widely-used tool for internet data collection. Consequently, Octopus Collector version 8.6.7 was employed to collect raw data using the template named “JD Reviews - Recent Reviews of Current Products.” Other fresh e-commerce platforms are only accessible via WeChat mini-programs, necessitating the creation of a Python program to collect comment data from these platforms.



Figure 3.1: Customer Review Interface

Source: Screenshot from the Dingdong Maicai APP, accessed on August 1, 2024

The version of Python used is Python 3.9.0. The process of obtaining sample data using web crawler technology is as follows: First, identify the required information. Starting from a target URL, parse the URL (Uniform Resource Locator) of the initial page and establish URL lists for four categories of fresh products. Second, parse and retrieve data. Sequentially traverse the links in the URL list until the loop command is completed, and use Python's data parsing module to parse the web page. Finally, store the data. After the system completes the information storage, the collected information is manually compiled, the data is summarized and sorted, and the sample data for this study is ultimately formed.

Figure 3.1 displays the customer review interface for a product. The customer's review includes details such as review content, review time, rating stars, customer name, product name, and membership level, among others. Subsequently, the collected data were imported into an Excel spreadsheet. The format of the gathered comment data is shown in Table 3.1.

Table 3.1: Example of Customer Comment on the Fresh e-commerce

Product Category	Vegetables
Product Name	Premium Tomato 500g
Customer Name	J*g
Membership Status	1
Rating	5
Comment Content	<i>The size is right, the flavor is pure, the price is reasonable, the packaging is beautiful, clean and tidy, the skin is thin, sweet and sour and juicy</i> <i>The tomatoes are very fresh, and the tomato scrambled eggs are very delicious.</i>
Number of Purchases	3
Time	2024-03-13
E-commerce Platform	Dingdong MaiCai

3.2.2 Data Cleaning

In this study, “Reviews Fetched (Before Cleaning)” denotes the complete set of review records retrieved within the collection window prior to any preprocessing. The count includes rating-only entries, posts that contain only emojis or only images, duplicated records arising from duplicated product listings, replies authored by sellers or by the platform system, and duplicates created by machine translation. Question and answer threads

are excluded. The term “review” refers to the review title and body combined. “Reviews Retained (After Cleaning)” refers to unique, consumer-authored textual comments that remain after applying the cleaning rules specified below.

Duplicate comments were identified and removed when the same account posted identical text multiple times or when the same review appeared across mirrored product listings. This procedure preserves the independence of observations and prevents particular viewpoints from being over-represented.

Records that do not contain analyzable text were excluded. This includes default auto-generated comments and posts composed only of numbers, emojis, images, links, coupon codes, or templated strings. Such content does not contribute meaningful information and increases noise in downstream analyses.

Comments were required to be written in Chinese and to meet a minimum length threshold of at least five Chinese characters. Very short comments rarely contain sufficient lexical information for reliable topic modeling and sentiment estimation. Comments that did not meet the threshold were removed.

Preprocessing was implemented in Python 3.9 using pandas (I/O and de-duplication), re (regular expressions), emoji (emoji detection/removal), jieba (tokenization when required for downstream checks), and hashlib (text fingerprints).

After applying these rules, the dataset was substantially refined. A total of 56,765 comments were retained from 77,183 reviews fetched, which corresponds to an overall retention rate of 73.5 percent. Table 3.2 reports the distribution by category and platform

using the column labels “Reviews Fetched (Before Cleaning)” and “Reviews Retained (After Cleaning).”

Table 3.2: Review Statistics of Collected Product Reviews

Product Category	Data Source	Reviews Fetched (Before Cleaning)	Reviews Retained (After Cleaning)
Vegetables	JD Fresh	4,659	4,096
	Dingdong MaiCai	4,346	3,032
	Taocaicai	5,500	3,770
	Yonghui Superstores	4,581	3,399
Fruits	JD Fresh	4,963	4,424
	Dingdong MaiCai	5,075	3,676
	Taocaicai	5,612	3,350
	Yonghui Superstores	4,487	3,009
Meat & Egg	JD Fresh	4,700	4,382
	Dingdong MaiCai	4,639	3,421
	Taocaicai	2,780	1,890
	Yonghui Superstores	5,473	4,045
Aquatic Products	JD Fresh	4,825	4,240
	Dingdong MaiCai	5,107	3,989
	Taocaicai	5,216	2,070
	Yonghui Superstores	5,220	3,972
Total		77,183	56,765

3.3 Data Processing

Customer review texts are converted into a structured indicator matrix through sentence-level topic assignment and sentiment scoring, followed by aggregation and scaling. Each clause in a review is treated as a separate document for topic modeling and is assigned a topic label; clause-level sentiment is then obtained from the sentiment service and mapped

to the relevant service-quality dimension via the topic–dimension map. The resulting aspect signals are aggregated at the observation level and assembled as observed variables for the latent constructs specified in the structural equation model. Figure 3.2 illustrates the standardization pipeline, and Tables 3.3 and 3.4 show the topic set, dimension mapping, and final observed-variable specification.

Customer reviews are noisy and unstructured text (Songpan, 2017). For example, *“Very very fresh, looked as if they just came off the plant, packed well for shipping, and very very large. Much larger than I’ve seen in the local stores here.”* The review has no fixed statement structure and also contains much irrelevant information (Somprasertsri & Lalitrojwong, 2010). These reviews are generated by customers using natural language, not structured data like values and categories. This means that the original customer reviews cannot be directly used for further data analysis. At the same time, this study uses a large number of customer reviews, which are difficult to read one by one manually. Therefore, it is necessary to automatically process the collected customer review data and convert the unstructured text into structured data.

The overall idea of data standardization in this study is presented below, with the framework for this process depicted in Figure 3.2.

In the data standardization process, all customer reviews are first split into individual sentences, each treated as an independent document for separate analysis. Bidirectional Encoder Representations from Transformers (BERTopic) technology is utilized for topic modeling, analyzing the topics discussed in the customer reviews, and assigning a specific topic to each sentence based on its content. This step is crucial for categorizing and organizing customer feedback, facilitating subsequent analysis and insight extraction.

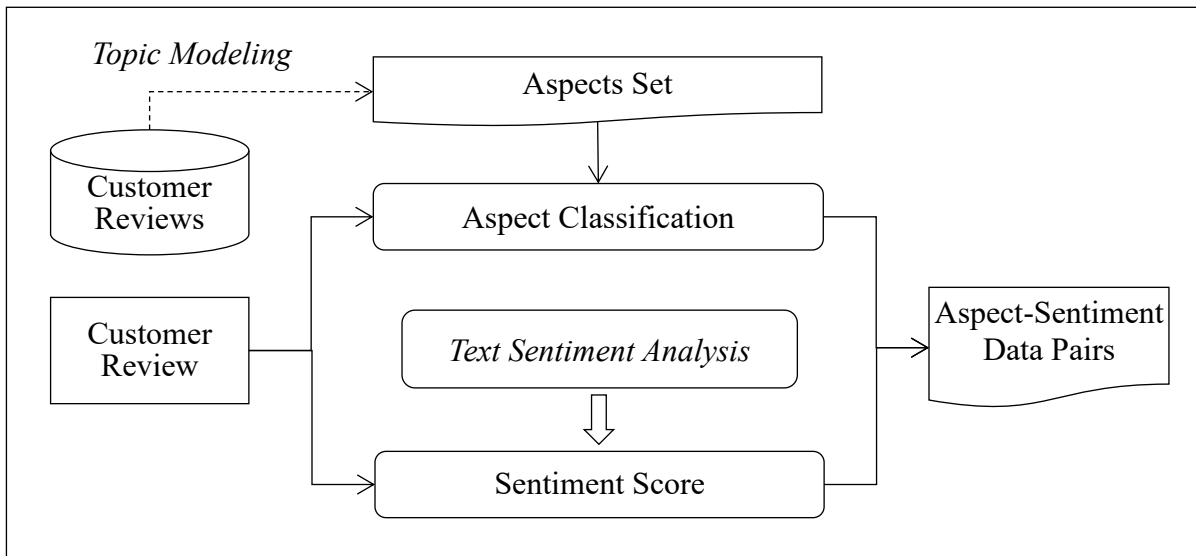


Figure 3.2: Framework for Data Processing of Customer Review

After identifying the topics, the next step is to conduct sentiment analysis on the content discussed under each topic. With the help of Baidu Smart Cloud's text sentiment analysis API, a sentiment score is obtained for each comment clause, ranging from -1 to 1, where -1 indicates negative sentiment and 1 indicates positive sentiment. By obtaining sentiment scores for each topic, a deeper understanding of customer perceptions towards different aspects of the products or services can be gained.

Finally, the last step in the data standardization process is to aggregate and collate the collected data. Each customer review is converted from its original unstructured form into a structured format, consisting of pairs of topics and their corresponding sentiment scores. By organizing the data in this way, analysis and conclusion drawing become more straightforward. It becomes easy to identify the aspects that are most important to customers and their perceptions of these aspects, enabling informed decisions to be made based on customer feedback.

3.3.1 Topic Modeling with BERTopic

This study explores customer concerns by analyzing customer review texts. In the analysis of consumer reviews, the word cloud model proves to be an effective visualization tool, skilled at accurately capturing and depicting the key concerns of consumers. After carefully segmenting the review text, numerous repetitive words become apparent. These high-frequency words are carefully summarized and sorted. The word cloud model utilizes an innovative design, intuitively mapping word frequency to font size within the word cloud visualization: words that appear more frequently in the reviews are displayed with larger fonts in the word cloud, thus attracting greater attention. This visual analysis technique enables a clear identification of the hotspots and key areas of focus within consumer reviews.

Orange is a Python-based data mining and machine learning platform widely utilized for text mining and visualization analysis. Its Word Cloud feature is a crucial component within the Orange Text Mining toolkit, designed to create word cloud visualizations from text data. This tool assists users in quickly identifying key terms and their frequency distributions within a dataset. Figure 3.3 presents the word cloud distribution derived from the collected reviews of fresh products, generated using the word cloud feature in Orange software. The top ten most frequent words are “fresh,” “quality,” “time,” “taste,” “price,” “product,” “packaging,” “portion,” “delivery,” and “service.”

Manually categorizing all 56,765 reviews into topics would be extremely time-consuming, but topic modeling can do this automatically in a few hours. Topic modeling is a method for unearthing the latent themes or “topics” within a collection of documents. It involves examining the text within these documents to detect patterns and relationships that indicate the presence of these topics. Over the past two decades, several topic modeling

techniques have been developed, each with unique strengths and theoretical foundations. Table 3.3 summarizes the most commonly used topic modeling approaches, along with their core features and sources.



Figure 3.3: Fresh Product Reviews Word Cloud
Source: Generated using the word cloud visualization feature in Orange

In analyzing short and informal customer reviews, it's essential to select a topic modeling method that can accurately capture semantic nuances and produce coherent themes. Traditional methods like LDA require the number of topics to be predefined and often struggle with short texts (Yan et al., 2013), resulting in overlapping or unclear topics. GSDMM, designed for short texts, improves topic compactness but still relies on word co-occurrence patterns and lacks deep contextual understanding (D. Q. Nguyen et al., 2015). Udupa et al. (2022) demonstrated that when applied to short review data, BERTopic generates more coherent and interpretable topics than GSDMM, thanks to its transformer-based semantic embedding and clustering approach. BERTopic also avoids the need to predefine the number of topics, increasing flexibility for exploratory research.

Table 3.3: Popular Topic Modeling Methods

Method	Description	Key Features	Author
Latent Dirichlet Allocation (LDA)	Probabilistic model assuming documents are mixtures of latent topics	Interpretable; requires pre-defined topic count	Blei et al. (2003)
Non-negative Matrix Factorization (NMF)	Matrix factorization technique for topic extraction	Stable output; based on TF-IDF	Lee and Seung (1999)
Structural Topic Model (STM)	Extension of LDA allowing inclusion of document-level covariates	Supports metadata; ideal for policy/social data	Roberts et al. (2014)
Gibbs Sampling Dirichlet Multinomial Mixture (GSDMM)	Dirichlet mixture model optimized for short texts	Suitable for short reviews or tweets	Yin and Wang (2014)
Top2Vec	Identifies topic clusters using document and word embeddings	Embedding-based; automatic topic detection	Angelov (2020)
Bidirectional Encoder Representations from Transformers Topic Model (BERTopic)	Combines BERT embeddings, UMAP reduction, and HDBSCAN clustering	No need to pre-define topics; high semantic quality	Grootendorst (2022)

Krishnan (2023) compared LDA, NMF, PAM, Top2Vec, and BERTopic using customer review datasets, and found that BERTopic consistently produced the most meaningful and coherent topics as measured by topic coherence scores. Egger and Yu (2022) evaluated performance across LDA, NMF, Top2Vec, and BERTopic applied to social media texts and demonstrated that BERTopic outperformed all others in interpretability and

relevance for short, informal user-generated texts. Given the fragmented and expressive nature of fresh food reviews, BERTopic offers a more reliable, nuanced, and user-friendly approach to uncovering service quality dimensions.

To ensure the model's suitability, a pilot test was conducted on a subset of 5,000 customer reviews from the dataset. This preliminary phase involved tuning hyperparameters (e.g., embedding models and minimum topic size) and evaluating topic coherence using metrics like C_v coherence score (Abuzayed & Al-Khalifa, 2021; Khodeir & Elghannam, 2025; Medvecki et al., 2023). The pilot test identified potential issues, such as over-fragmentation of topics in short comments (comprehension problems) and inconsistent clustering patterns across platforms (response patterns), which were mitigated by adjusting the UMAP dimensionality reduction and HDBSCAN clustering parameters (Li et al., 2024; Nanyonga et al., 2025).

BERTopic (Grootendorst, 2022) is an advanced topic modeling technique based on BERT (Bidirectional Encoder Representations from Transformers) (Rogers et al., 2021). It employs various embedding techniques and Class-based Term Frequency-Inverse Document Frequency (c-TF-IDF) to form dense clusters, enabling easily interpretable topics while retaining important words in the topic descriptions. It can analyze latent topics within clusters of varying densities and extract the most relevant keywords for each topic.

BERTopic has been applied in a variety of contexts, demonstrating its effectiveness and versatility. Lindelöf et al. (2023) utilized the BERTopic model to extract discussion topics from negative tweets regarding COVID-19 vaccines. Najmani et al. (2023) employed BERTopic technology to conduct thematic analysis on the subtitles of courses available on the MOOC platform Coursera, successfully extracting and identifying multiple key topics

from these subtitle texts. Scarpino et al. (2022) compared various topic modeling techniques and found that the BERTopic method significantly outperformed the traditional LDA approach. Specifically, BERTopic accurately assigned up to 97.26% of the analyzed documents to the corresponding topic clusters, with an overall analysis accuracy of 91.97%. Given these findings, this study utilizes BERTopic to perform topic modeling on the collected customer reviews, thereby extracting meaningful latent variables and effectively elucidating the service quality of fresh e-commerce.

To enhance topic granularity and reduce semantic overlap, each of the 5,6765 customer reviews was segmented into smaller semantic clauses based on Chinese punctuation rules (e.g., commas, periods, and coordinating conjunctions). This clause-level segmentation yielded a total of 235,131 clauses, averaging 4.14 clauses and 7.5 characters per review. For example, a review like “The vegetables were fresh, delivery was fast, but the ice pack was missing, and some items arrived bruised” would be segmented into: [“The vegetables were fresh”, “Delivery was fast”, “But the ice pack was missing”, “Some items arrived bruised”].

Each clause was then transformed into a dense semantic vector using the multilingual pre-trained model “paraphrase-multilingual-MiniLM-L12-v2” from the Sentence-Transformers library (Reimers & Gurevych, 2019). This model outputs a 384-dimensional embedding that captures the semantic similarity between short texts across more than 50 languages, including Chinese. The resulting matrix had a size of $235,131 \times 384$.

To improve computational efficiency while preserving semantic structure, the high-dimensional embeddings were reduced to 5 dimensions using Uniform Manifold Approximation and Projection (UMAP) (McInnes et al., 2018). This low-dimensional

representation preserves local and global relationships between clauses, facilitating better clustering performance.

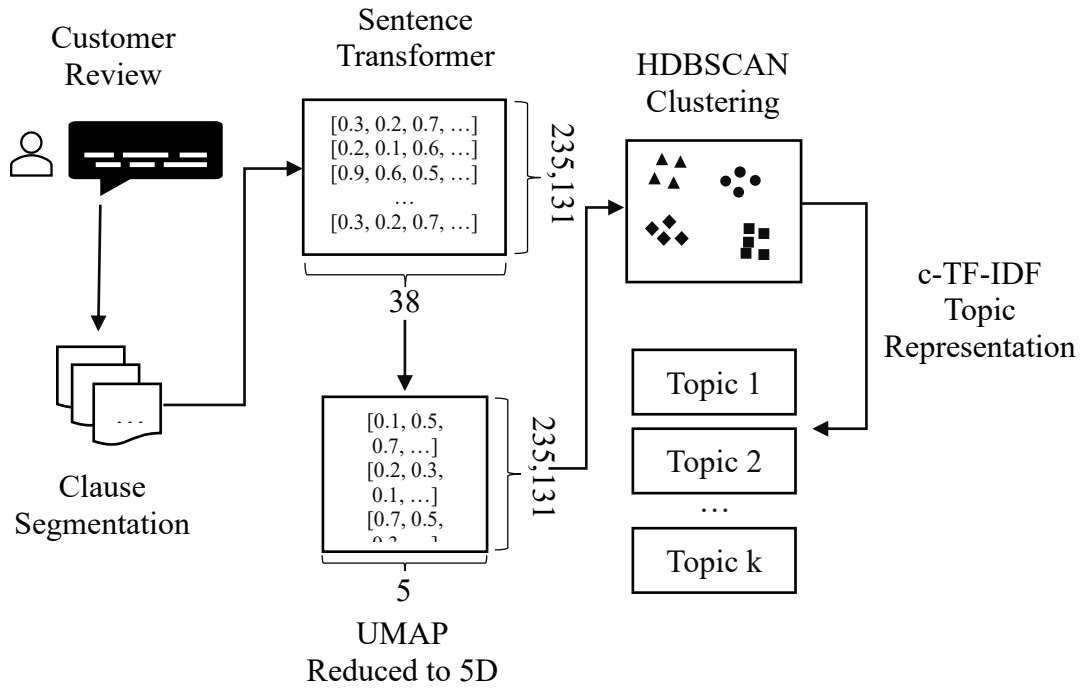


Figure 3.4: BERTopic Framework

Subsequently, the reduced embeddings were clustered using Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) (Campello et al., 2013). This density-based algorithm automatically determines the number of clusters. The minimum cluster size was set to 15 to ensure each topic contained a meaningful amount of content and to suppress noise from outliers or marginal clauses.

Finally, topic labels were generated using class-based TF-IDF (c-TF-IDF), which treats all clauses within a cluster as a single document and extracts keywords that are frequent within the cluster but rare across others (Grootendorst, 2022).

Figure 3.4 illustrates the overall process of extracting service quality topics from customer reviews.

3.3.2 Validation of Topic Modeling Outputs

The indicators that feed into the subsequent structural equation model must be interpretable, distinct, and reproducible. Topic modeling can be sensitive to parameter choices and stochastic components, which makes explicit validation necessary. Semantic coherence quantifies within topic interpretability and aligns with human judgments of topic quality, thereby supporting face validity of the learned representations (Chang et al., 2009; Lau et al., 2014; Röder et al., 2015). Topic diversity assesses redundancy across topics and complements coherence to ensure that themes are well separated, a criterion widely adopted in neural and embedding based topic models for model selection (Dieng et al., 2020). Stability addresses reproducibility by examining whether similar topics and assignments are recovered under resampling and different random initializations, which provides evidence analogous to test retest reliability and guards against configuration specific artifacts (Greene et al., 2014; Webber et al., 2010). Together, the three diagnostics map onto core principles of measurement quality required before estimating the measurement and structural components of the model.

Semantic coherence was used to evaluate the degree to which the most probable words within a topic form a semantically consistent set (Lau et al., 2014; Röder et al., 2015). The C_v measure was computed with a sliding window and normalized pointwise mutual information using the standard implementation in Gensim, following the procedures in Röder et al. (2015). Reporting uses the top ten words per topic, which is consistent with prior practice in Lau et al. (2014). Higher C_v values indicate stronger within topic semantic relatedness and greater human interpretability. In line with Lau et al. (2014), C_v values at or above approximately 0.45 are considered acceptable for exploratory applications, and coherence is compared across alternative parameterizations to ensure that a single setting

does not drive conclusions. To mitigate specific bias, results are cross-checked with a pointwise mutual information-based coherence variant where appropriate.

Topic diversity was used to assess the redundancy of vocabulary across topics and the distinctiveness of themes. Diversity was calculated as the proportion of unique words among the top N words across all topics (Dieng et al., 2020).

$$\text{Topic Diversity} = (\text{Number of unique words across all topics}) / (K \times N)$$

where K is the number of topics and N is the number of top keywords per topic (in this study, $N = 10$). Larger values indicate lower overlap of salient vocabulary and more precise separation between themes. Diversity is reported alongside coherence and is used for model selection in neural and embedding-based topic models. Values close to 0.90 or higher are typically interpreted as indicating low redundancy.

Stability was examined under random reinitializations and corpus resampling (Hoyle et al., 2021). Two independent runs with different random seeds and one bootstrap resample at eighty percent of the corpus were fitted under the same configuration (Greene et al., 2014). Topics across runs were aligned by maximum weight bipartite matching on pairwise similarity. Similarity was quantified in two ways to capture both ranking sensitivity and set overlap. First, rank biased overlap was used on the ordered lists of the top ten words for each topic (Webber et al., 2010). Second, Jaccard similarity was used on the unordered sets of the top ten words. The average matched similarity across runs summarizes topic stability at the word level. In addition, document assignment stability was assessed using the Adjusted Rand Index between clusterings from different runs, which summarizes agreement after adjusting for chance (Hubert & Arabie, 1985). Stability was considered acceptable when the between-

run change in mean C_v was ≤ 0.02 , the average Jaccard overlap of top-10 words was ≥ 0.60 , and the Adjusted Rand Index (ARI) was ≥ 0.50 .

3.3.3 Aspect-Based Sentiment Analysis

Customer reviews typically comprise one to several short sentences, each containing the aspect of the review and the resulting emotion. To convert customer reviews into structured data that is easily processable, the following steps are necessary. Firstly, each customer review is split into multiple clauses and labeled with topic classifications based on BERTopic topic modeling technology. Secondly, text sentiment analysis technology is utilized to determine the sentiment score of each clause.

3.3.3.1 Customer Review Sentence Segmentation

Once BERTopic finishes topic modeling, it allocates one or more topic labels to each document, relying on the topic candidate words and the weights assigned to each cluster. These topic labels signify the primary content or the discussed topic of the document, thus accomplishing document topic classification (Grootendorst, 2022). Online reviews constitute informal speaking contexts where customers frequently use brief sentences to convey their opinions. Consequently, customer reviews generally consist of multiple phrases. In this study, each clause within a review is regarded as a document during the BERTopic topic modeling process. Upon completion of the topic modeling, each clause in the comment is categorized into a corresponding topic.

Table 3.4 presents the outcomes of sentence segmentation and sentence topic classification for the customer review: “beautiful packaging, good taste, very good shopping, the delivery speed is very fast, the merchant has a very good service attitude, very satisfied with a shopping.”

Table 3.4: Example of Sentence Segmentation and Sentence Topic Classification

ReviewID	Review Cut Unit	TopicID
178	beautiful packaging	12
178	good taste	3
178	very good shopping	11
178	the delivery speed is very fast	7
178	the merchant has a very good service attitude	14
178	very satisfied with a shopping	9

3.3.3.2 Text Sentiment Analysis

Sentiment analysis is a burgeoning area that bridges linguistics and computer science. A key technology enabling the sentiment analysis of text is Natural Language Processing (NLP), a sub-discipline of Artificial Intelligence that equips computer systems to understand the diverse languages used by humans for communication. It can read free-form text and convert it into an analyzable format (Yi & Liu, 2020). By integrating machine learning with NLP, systems can automatically ascertain whether a text is positive, negative, or neutral, assigning polarity or weighted sentiment scores to entities within the text (Alrehili & Albalawi, 2019).

Sentiment analysis is valuable for inferring people's emotions. Balahur et al. (2013) utilized it to extract news opinions from newspaper articles. Nguyen et al. (2015) have built sentiment analysis models that leverage social media sentiment to forecast stock price movements, resulting in a 2.07% improvement in accuracy compared to models relying solely on historical prices. Salehan and Kim (2016) explored the usefulness and readership of online customer reviews on Amazon.com, employing sentiment analysis to uncover the

underlying sentiment in customer reviews and examine how other variables influence the significance of these reviews. B2C online pharmacy reviews were analyzed to assess the emotions conveyed in the reviews, aiding online pharmacy businesses in identifying factors that boost customer satisfaction (Liu et al., 2020). The sentiment analysis technique utilizing support vector machines demonstrated high accuracy in determining the sentiment of tweets about Traveloka, a travel service mobile app, achieving an accuracy rate of 82.5% (Dieksona et al., 2023).

Given the extensive range of real-life application scenarios and the strong demand for sentiment analysis, its commercial potential is particularly immense. Consequently, numerous prominent Internet companies in China, including Baidu, Alibaba, Tencent, and JD.com, have energetically invested in the research and development of sentiment analysis technology, subsequently launching their proprietary sentiment analysis API services. Tang et al. (2020) compared seven popular Chinese sentiment tools and found Baidu's API to be the most accurate, especially for short, user-generated content like e-commerce reviews. It handles strong emotions and colloquial language better than others, making it ideal for commercial sentiment analysis.

This study utilized the sentiment analysis API offered by Baidu to quantify the sentiment score of comment clauses (https://ai.baidu.com/tech/nlp_apply/sentiment_classify). This API incorporates an advanced Bi-LSTM (bidirectional long short-term memory network) sentiment classification model, which ascertains sentiment by thoroughly comprehending text semantics, thereby effectively circumventing the inherent constraints of traditional feature engineering classification methods. Zhao et al. (2022) computed the COVID-19 public opinion index using Baidu's sentiment analysis API, based

on 200,000 text entries from Sina Weibo. Zhang et al. (2021) randomly selected 200 Weibo comments and manually labeled them with their corresponding sentiment states. The manual labeling results were then compared to the labels automatically produced by Baidu's sentiment analysis API. The findings revealed that the API exhibited a 92% accuracy rate in sentiment analysis.

The output of Baidu's sentiment analysis API comprises sentiment classification (0: negative, 1: neutral, 2: positive) along with the corresponding probabilities (within the range [0,1]). Figure 3.5 presents the Python code for utilized to compute the sentiment score of the review phrase "*the merchant has a very good service attitude*" using Baidu sentiment analysis API.

To accurately quantify the sentiment tendency in comments, this study has devised a straightforward method for numerically expressing sentiment polarity: positive sentiment is represented by positive numbers, while negative numbers represent negative sentiment. Specifically, after evaluating the positive review "*the merchant has a very good service attitude*" using Baidu's sentiment analysis API, a sentiment score of 0.934825, indicating positive sentiment probability, is obtained. Conversely, the negative review "*It's so different from the description*" yields a sentiment score of -0.999816, which is the negative value of its negative sentiment probability. Neutral reviews, such as "*nothing special*", are uniformly represented by a score of 0.

```

import requests
import json

API_KEY = "NmVJjc***vyKAXK"
SECRET_KEY = "Ql5hpw***KNszR8"

def main():

    url = "https://aip.baidubce.com/rpc/2.0/nlp/v1/sentiment_classify?charset=UTF-8&access_token=" + get_access_token()

    payload = json.dumps({
        "text": "the merchant has a very good service attitude"
    })
    headers = {
        'Content-Type': 'application/json',
        'Accept': 'application/json'
    }

    response = requests.request("POST", url, headers=headers, data=payload)

    print(response.text)

def get_access_token():
    """
    使用 AK, SK 生成鉴权签名 (Access Token)
    :return: access_token, 或是None(如果错误)
    """
    url = "https://aip.baidubce.com/oauth/2.0/token"
    params = {"grant_type": "client_credentials", "client_id": API_KEY, "client_secret": SECRET_KEY}
    return str(requests.post(url, params=params).json().get("access_token"))

if __name__ == '__main__':
    main()

{
  "text": "the merchant has a very good service attitude",
  "items": [
    {
      "confidence": 0.855166,
      "negative_prob": 0.0651753,
      "positive_prob": 0.934825,
      "sentiment": 2
    }
  ],
  "log_id": "1839863961811886802"
}

```

Figure 3.5: Python Code to Call Baidu Sentiment Analysis API
Source: Developed by the author using Python 3.9.0

3.3.3.3 Validation of Sentiment Analysis

This section evaluates the reliability of two automated outputs: whether each clause is assigned to the correct topic in line with human understanding of its main content, and whether clause-level sentiment polarity aligns with human judgments. Validation follows the use of a human-annotated gold standard, consistent with established practice in

computational linguistics for corpus annotation and reliability reporting (Artstein & Poesio, 2008).

The audit sample for joint validation of clause sentiment and clause→topic assignment comprises $n = 180$ clauses, drawn via stratified sampling across topic $\times$ platform $\times$ product category. The size of 180 is motivated by coverage and balance (Newcombe, 1998): selecting 10 clauses per learned topic (18 topics) ensures that every topic has sufficient human-checked instances for per-topic accuracy estimation and avoids topic-level evaluation bias. From a precision standpoint, assuming an expected overall accuracy of 0.80, $n = 180$ yields an approximate 95% confidence interval with a half-width of ± 6 percentage points using single-proportion interval methods, which is adequate for an audit-style check.

A written codebook (Artstein & Poesio, 2008) is used to reduce subjectivity and support reproducibility. It specifies decision rules for topic assignment (emphasizing identification of the evaluation object: received item, delivery process, after-sales support, platform usability, or price/value) and for sentiment polarity (covering negation, contrast, degree adverbs, mild sarcasm, and numeric/measure expressions). Two trained annotators, blinded to system outputs, independently label each clause with one best topic ID and a three-class sentiment label (negative/neutral/positive). Inter-annotator reliability is quantified with Cohen’s κ for both topic and sentiment; $\kappa \geq 0.70$ is interpreted as substantial agreement (Cohen, 1960; Landis & Koch, 1977). Disagreements are adjudicated to produce consensus (adjudicated) labels, which serve as the gold standard for evaluation.

For topic assignment, overall performance is reported using Top-1 accuracy. For sentiment classification, overall accuracy is reported; per-class precision, recall, and F1 (negative/neutral/positive) are also provided to reveal potential asymmetries. To document

human reliability, Cohen's κ (and percentage agreement) for both sentiment and topic are included. These metrics and reporting conventions follow standard practice for multi-class evaluation in Natural Language Processing (Powers, 2020; Sokolova & Lapalme, 2009). As pragmatic acceptance guidelines in this context, performance is considered adequate when accuracy ≥ 0.80 and annotator $\kappa \geq 0.70$ (Landis & Koch, 1977).

3.3.4 From Text to SEM Indicators

This subsection explains how clause-level outputs from topic modeling and sentiment scoring are transformed into observed variables for the latent constructs and then aggregated to a product-level dataset for structural equation modeling.

Using 56,765 cleaned reviews, the model identified eighteen interpretable topics (Table 3.5). Topics are mapped to the conceptual dimensions defined in Chapter 2 (Fresh E-commerce Service quality dimensions, Customer Satisfaction, Repurchase Intention) by inspecting representative words and exemplar clauses, a common practice when linking unsupervised topics to higher-level constructs.

For neural and embedding-based topic models, topic sets are typically selected and organized using coherence and diversity diagnostics (reported in Section 3.3.2), after which topics can be consolidated into measurement indicators aligned with theory.

Star rating is included as an observed indicator of Customer Satisfaction because it captures overall evaluative judgments in online reviews and is widely used in recent research (Baker & Hashimoto, 2024; Zhao et al., 2019). For Repurchase Intention, two behavioral proxies are incorporated: membership status (coded 1 for members and 0 for non-members) and the number of purchases extracted from the review context, where available.

Membership signals engagement with loyalty programs and is associated with repeat behavior in recent empirical work (Myftaraj & Trebicka, 2023). These non-text signals complement text-derived indicators from topic-mapped aspects.

Table 3.5: Topics Extracted Using BERTopic from Customer Review

Topic	Count	Representative_Words	Dimension
0	21950	Quality, Product, Performance, Description	Fulfillment
1	20048	Weight, Net Weight, Size, Pound	Fulfillment
2	14651	Fresh, Bad Fruit, Lively, Strange Smell	Fulfillment
3	11976	Taste, Sweet, Delicious, Unpalatable	Fulfillment
4	6240	Bad Review, Disappointing, Too Bad, Waste,	Customer Satisfaction
5	5681	Repurchase, Buy, Good value, Multiple times	Repurchase Intention
6	5673	Happy, Family, Worry, Like	Customer Satisfaction
7	4893	Express Delivery, Door-To-Door Delivery, On Time, Fast	Logistics Service Quality
8	4872	After-sales, Refund, Last time, Return	Customer Service
9	4855	Satisfied, Good Review, Great, Very Good	Customer Satisfaction
10	4850	Recommend, Colleague, Highly Recommend, Improve	Repurchase Intention
11	4399	Shopping, Strenuous, Suitable, Cooking	Ease of Use
12	4247	Cold Chain, Ice Pack, Freezing, Insulated Box	Logistics Service Quality
13	4155	Cost-Effective, Cheap Price, Good Quality, Low Price, Price Ratio	Economic Efficiency
14	4073	Service Attitude, Merchant, Store, Customer	Customer Service
15	3935	Packaging, Plastic Bag, Packaging Bag, Packaging Box	Logistics Service Quality
16	3082	Easy, Clean, Sanitary, Well Handled	Ease of Use
17	1536	Convenient, Mall, Experience, Daily	Ease of Use

Observed variables are grouped by latent construct as specified in Table 3.6: Fulfillment (A1–A4 from T0, T2, T1, T3), Ease of Use (B1–B3 from T11, T16, T17), Customer Service (C1–C2 from T8, T14), Logistics Service Quality (D1–D3 from T7, T12, T15), Economic Efficiency (E1 from T13), Customer Satisfaction (S1–S3 from T9, T4, T6 plus S4 as star rating), and Repurchase Intention (R1–R2 from T5, T10 plus R3 as membership status and R4 as number of purchases).

Each review is segmented into clauses. For each clause, the assigned topic defines its aspect, and the sentiment tool returns a polarity score in $[-1,1]$, which is then associated with that aspect for downstream use (Section 3.3.3). Aspect-based sentiment analysis at clause or sentence granularity is a standard approach in recent literature and supports fine-grained operationalization of constructs from user-generated reviews (Brauwers & Frasincar, 2022; Zhang et al., 2022).

Table 3.6: Variable Description

Latent Variables	Comment Topics	Observed Variables
Fulfillment	T0, T2, T1, T3	A1, A2, A3, A4
Ease of Use	T11, T16, T17	B1, B2, B3
Customer Service	T8, T14	C1, C2
Logistics Service Quality	T7, T12, T15	D1, D2, D3
Economic Efficiency	T13	E1
Customer Satisfaction	T9, T4, T6, Rating	S1, S2, S3, S4
Repurchase Intention	T5, T10, Membership Status, Number of Purchases	R1, R2, R3, R4

When a review does not mention an aspect j , the corresponding entry is treated as structurally missing rather than as a zero sentiment value. This follows current

recommendations to distinguish “not applicable / not observed” from true zeros in downstream aggregation and avoids attenuating product-level signals (Pham et al., 2024). In subsequent aggregation, only non-missing aspect scores are averaged for each product–indicator cell (Zhou et al., 2024).

Let i index products, $r \in R_i$ the reviews of product i , and j an observed indicator derived from topics. Product-level text-based aspect indicators are calculated as the average of non-missing clause scores for aspect j within product i .

$$X_{ij} = \frac{1}{n_{ij}} \sum_{r \in R_i} s_{rj} * 1 \{j \text{ mentioned in } r\}$$

$$n_{ij} = \sum_{r \in R_i} 1 \{j \text{ mentioned}\}$$

Star ratings are averaged at the product level; membership status and number of purchases are averaged over reviews that report them (interpretable, respectively, as member share and mean purchases). This “average over non-missing” aggregation is consistent with recent practice that summarizes topic or aspect signals across review sets to characterize products or assortments (Banerjee et al., 2021). To ensure sufficient information per cell, an indicator is retained for product i only if $n_{ij} \geq 3$. Table 3.7 illustrates the standardized review-level matrix, and Table 3.8 presents an example of the resulting product-level dataset (311 products retained after listwise screening).

Table 3.7: Example of Customer Reviews After Initial Standardization

Proudct_ID	Review_ID	Fulfillment				Ease of Use			Customer Service		Logistics Service Quality			Economic Efficiency	Customer Satisfaction				Repurchase Intention			
		A1	A2	A3	A4	B1	B2	B3	C1	C2	D1	D2	D3	E1	S1	S2	S3	S4	R1	R2	R3	R4
P1	2		0.89	0.98	0.91								0.93	0.82				5			1	8
P1	3					0.58			0.57				0.46		0.54			3		2	0	1
P1	4	0.21	-0.95	-0.25		-0.07				-0.19			-0.02	0.54			0.65	4	3		0	2
P1	5							-0.2	0.03	0.71						0.82		4			0	5
P1	6	-0.36			-0.02	-0.25				-0.96	-0.26		-0.15					1	5		1	4
P2	23					-0.06						0.93	-0.58	0.8	0.21	0.31		1	3	3	0	5
P2	24	-0.77	-0.35	-0.87		0.04				-0.7	0.41	-0.81						3	5		0	2
P2	25		0.54		-0.63		-0.38		0.39	0.41					0.63			4		2	1	3
P2	26	-0.17	0.51						0.34	-0.7			0.09					2		2	0	5
P3	624					0.58			0.57				0.46		0.34			3		2	0	1
P3	625	0.21	-0.95	-0.25		-0.07				-0.19			-0.02	0.54			0.57	4	3		0	2
P3	626							-0.2	0.03	0.71						0.72		4			0	5

Table 3.8: Example of Customer Reviews After Final Standardization

Proudct_ ID	Fulfillment				Ease of Use			Customer Service		Logistics Service Quality			Economic Efficiency	Customer Satisfaction				Repurchase Intention			
	A1	A2	A3	A4	B1	B2	B3	C1	C2	D1	D2	D3	E1	S1	S2	S3	S4	R1	R2	R3	R4
P1	-0.08	-0.03	0.37	0.45	0.09	0.00	-0.20	0.30	-0.15	-0.26	0.00	0.31	0.68	0.54	0.82	0.65	3.40	4.00	2.00	0.40	4.00
P2	-0.47	0.23	-0.87	-0.63	-0.01	-0.38	0.00	0.37	-0.33	0.41	0.06	-0.25	0.80	0.42	0.31	0.00	2.50	4.00	2.33	0.25	3.75
P2	0.21	-0.95	-0.25	0.00	0.26	0.00	-0.20	0.30	0.26	0.00	0.00	0.22	0.54	0.34	0.72	0.57	3.67	3.00	2.00	0.00	2.67

3.4 Data Analysis

In the domain of empirical research, the complexity of certain constructs frequently prevents direct observation. For example, when exploring the interrelationships between constructs like excellence, satisfaction, health, fairness, and optimism, direct measurement is not possible. Rather, these constructs must be deduced through readily observable indicators. These unobservable constructs are referred to as latent variables, whereas the observable indicators act as their representatives, known as manifest variables. Traditional statistical methods, such as regression, correlation, and analysis of variance, are inadequate for analyzing relationships involving latent variables because they cannot account for measurement error and the complex interdependencies among constructs. Structural equation modeling (SEM) presents itself as a resilient alternative, providing a comprehensive framework for concurrently estimating the relationships between latent variables and their corresponding manifest indicators (Lei & Wu, 2007).

3.4.1 Assumption Tests

Text-derived indicators for all latent constructs are produced from clause-level topic assignment and aspect-based sentiment scoring, then aggregated at the product level as specified in Section 3.3 (see Table 3.7). To ensure a minimum information content and reduce attenuation, the same mention threshold is retained (cells with fewer than three valid clause mentions for a given aspect are screened out), and all indicators are standardized prior to estimation; the inclusion of non-text proxies (average star rating for Customer Satisfaction; membership share and mean purchases for Repurchase Intention) follows best practice for modeling digital-trace constructs and diversifying measurement sources (Blei et al., 2010; Grimmer & Stewart, 2013).

Outliers are screened in two layers. For univariate outliers, observations are flagged using standardized scores with a strict $|z| > 3.29$ screen, which is commonly recommended in SEM diagnostics (Kline, 2023b). For multivariate outliers, Mahalanobis distance is computed as $D^2 = (x - \bar{x})^T S^{-1} (x - \bar{x})$ and referenced to the χ_p^2 distribution with degrees of freedom equal to the number of indicators; cases with $p < .001$ are inspected for text-processing artifacts and documented (retain/correct/remove) to preserve replicability.

Distributional assumptions are assessed at both marginal and joint levels. For each indicator, skewness and kurtosis summarize univariate shape. For joint normality, Mardia's multivariate kurtosis is computed and interpreted via its standardized statistic, which is the standard omnibus test for multivariate normality in covariance-based SEM (Kline, 2023b; Mardia, 1974). If non-normality is indicated, global fit is evaluated using the Bollen–Stine bootstrap p-value, and inference on indirect effects relies on non-parametric bootstrap with bias-corrected confidence intervals, which is appropriate for non-Gaussian sampling distributions (Bollen & Stine, 1992; Preacher & Hayes, 2008).

Before estimating structural paths, multicollinearity among exogenous constructs is examined using construct-level Variance Inflation Factors (VIF) computed from composite or preliminary factor-score proxies; a conservative working threshold of $VIF < 3.3$ is adopted, and pairs with inter-construct correlations $\gtrsim .85$ trigger conceptual overlap checks or respecification (Sarstedt, 2019).

3.4.2 Measurement Model

Service-quality constructs include Fulfillment (FUL), Ease of Use (EOU), Logistics Service Quality (LSQ), Customer Service (CUS), and Economic Efficiency (EE). FUL uses four reflective indicators that summarize quality, accuracy, taste, and freshness. EOU uses three indicators for navigation, checkout, and convenience. LSQ uses three indicators for delivery speed, cold-chain integrity, and packaging. CUS uses two indicators for after-sales or refund handling and service attitude. EE enters the baseline model as a single observed composite. Outcomes are Customer Satisfaction (CS), measured by three text-based satisfaction indicators plus the average star rating, and Repurchase Intention (RI), measured by two text-based intent indicators plus membership share and mean purchases, both standardized as continuous proportions or rates. Topic-to-dimension mapping follows the codebook in Section 3.3, and coherence, diversity, and stability diagnostics provide prior evidence of content validity (Lau et al., 2014; Röder et al., 2015).

Before estimating the structural model, a confirmatory factor analysis (CFA) was conducted on the six multi-item constructs. Economic Efficiency (EE) was treated as an observed variable in the subsequent structural model and therefore was excluded from the CFA and from reliability/validity assessment. The sample size was $N = 311$, and maximum likelihood (ML) estimation was employed in AMOS. Each indicator loaded only on its designated latent factor, and latent factors were freely correlated. Global model fit was evaluated with CMIN/DF (χ^2/df), GFI, NFI, CFI, TLI, and RMSEA (90% confidence interval). Interpretation followed conventional SEM guidelines (Hu & Bentler, 1998; Kline, 2023b). Convergent validity was examined via standardized loadings, Composite Reliability (CR), and Average Variance Extracted (AVE). Discriminant validity was assessed using the Fornell–Larcker criterion.

3.4.3 Model Estimation and Fit

The structural model treats Fulfillment (FUL), Ease of Use (EOU), Customer Service (CUS), Logistics Service Quality (LSQ), and Economic Efficiency (EE) as exogenous and mutually correlated latent or composite predictors (covariances freely estimated), with directed paths from each antecedent to Customer Satisfaction (CS) and to Repurchase Intention (RI), and a path $CS \rightarrow RI$ to permit simultaneous estimation of direct and indirect mechanisms in a single system (Bollen & Stine, 1992; Kline, 2023b).

With p observed indicators, the free-parameter count t satisfies $t \leq p(p+1)/2$; reflective factors are scaled by fixing one loading to 1, and all first-order factors are locally identified under this scaling (Bollen & Stine, 1992; Kline, 2023b). Allowing exogenous covariances mitigates omitted-covariance bias in path estimates.

Parameters are estimated by maximum likelihood (ML) with FIML for missingness at the product level (Enders, 2022; Kline, 2023b; Yuan & Bentler, 2006). When distributional diagnostics (skew/kurtosis and Mardia's statistic) indicate non-normality typical of text-derived aggregates, Bollen–Stine bootstrap p-values support global-fit inference, and bootstrap standard errors are used for tests of paths and indirect effects; robust corrections may be additionally reported (Savalei & Bentler, 2006; Yuan & Bentler, 2006). Latent variables are scaled by the reference-loading method; model matrices include the exogenous covariance block and the structural coefficient matrix per the specified graph (Kaplan & Nieschwietz, 2003; Maruyama, 1997).

Mediation is evaluated inside the SEM using non-parametric bootstrapping with 5,000 resamples and bias-corrected 95% confidence intervals (Kline, 2023b; Preacher & Hayes, 2008). For each antecedent X , the following quantities are reported: a (path $X \rightarrow CS$),

b (path $CS \rightarrow RI$), c' (direct $X \rightarrow RI$ controlling CS), ab (indirect), and $c = c' + ab$ (total). An indirect effect is considered present when the bootstrap CI for ab excludes zero (Preacher & Hayes, 2008). Mediation form is summarized using the Zhao et al. (2010) taxonomy: *complementary mediation* when ab and c' are both significant with the same sign; *indirect-only* when ab is significant and c' is not.

Model fit is evaluated jointly by CMIN/DF (χ^2/df), GFI, NFI, CFI, TLI, and RMSEA (with 90% CI), interpreted with widely adopted, non-mechanistic guidelines that consider sample size and model complexity (Hu & Bentler, 1998; Kline, 2023b). Post-hoc modification indices are consulted only when consistent with theory (e.g., a justified correlated uniqueness); any freed parameter is documented together with its rationale and the change in fit and substantive interpretation (Byrne, 2010; MacCallum, 1986).

3.5 Summary

This chapter has provided a comprehensive overview of the research methodology adopted in the study. It defines the data window as August 2023 to August 2024 and the sampling frame across four Chinese fresh e-commerce platforms (JD Fresh, Dingdong MaiCai, Yonghui Superstores, Taocaicai), stratified by platform and category (fruits, vegetables, meat and eggs, aquatic products) with best-selling products selected in each stratum. Reviews were collected using Octopus Collector where applicable and Python 3.9 routines for platforms accessed via mini-programs. The chapter details cleaning and preprocessing rules, including Chinese-language filtering, a minimum length of five Chinese characters after normalization, duplicate handling, and text normalization. Unstructured reviews were transformed into structured indicators through clause segmentation, BERTopic topic assignment, aspect-based sentiment scoring with the Baidu API, and aggregation at the

product level, with coherence, diversity, and stability diagnostics reported. Measurement and structural analysis employed covariance-based SEM: reflective blocks for multi-indicator constructs, and mediation testing through Customer Satisfaction using nonparametric bootstrap.

The research questions are addressed with a covariance-based structural equation model estimated after the measurement model has been validated. Exogenous constructs include Fulfillment (FUL), Ease of Use (EOU), Logistics Service Quality (LSQ), Customer Service (CUS), and Economic Efficiency (EE). Covariances among exogenous constructs are freely estimated. Directed paths are specified from each antecedent to Customer Satisfaction (CS) and to Repurchase Intention (RI), and from CS to RI. RQ1 (effects of service-quality dimensions on CS) is answered by the standardized path coefficients from FUL, EOU, LSQ, CUS, and EE to CS, reported with ML estimates, standard errors, p values, 95% bootstrap confidence intervals, and explained variance $R^2(\text{CS})$. RQ2 (direct effects on RI) uses the corresponding paths from all antecedents to RI and reports $R^2(\text{RI})$. RQ3 (the CS $\rightarrow$ RI link) is tested via the structural path from CS to RI in the same system. RQ4 (mediation through CS) is evaluated within the SEM using nonparametric bootstrapping with 5,000 resamples and bias-corrected 95% confidence intervals for each antecedent X . The indirect effect $X \rightarrow \text{CS} \rightarrow \text{RI}$ is reported alongside the direct effect $X \rightarrow \text{RI}$ that controls CS and the total effect. Mediation form is classified by whether the indirect confidence interval excludes zero and by the significance of the direct path. For descriptive context, the variance accounted for ($\text{VAF} = \text{indirect}/\text{total}$) is also presented. Model adequacy for answering all research questions is documented by CMIN/DF (χ^2/df), GFI, NFI, CFI, TLI, and RMSEA.

CHAPTER 4

EMPIRICAL RESULTS & FINDINGS

4.1 Introduction

This chapter presents the empirical results and findings of the research, focusing on the intricate relationships among online service quality, customer satisfaction, and repurchase intention in the context of Chinese fresh e-commerce. By utilizing a comprehensive dataset obtained from customer reviews across multiple platforms, this study applies advanced analytical techniques, including descriptive statistics, topic modeling, and structural equation modeling (SEM), to reveal the underlying dynamics driving customer behavior.

4.2 Data Overview

The data for this study were collected from valid customer comments on a total of 311 products available across four major platforms: JD Fresh, Dingdong Maicai, Yonghui Superstores, and Taocaicai. These products span a wide range of categories, including fruits, vegetables, meat & eggs, and aquatic products, ensuring a comprehensive dataset for analysis.

Table 4.1 provides an overview of the customer review data, detailing the products covered in each category, the number of products in each category, and the corresponding comment count.

Table 4.1: Data Overview of Customer Review

Category	Representative Products	Quantity of Products	Comment Count
Fruits	Grapes, Bananas, Apples, Oranges, Pears, Dates, Dragon Fruit, Watermelon, Kiwi, Pomegranate, Cherry, Mangosteen, Prunes, Jackfruit	74	14,459
Vegetables	Green Vegetables, Potatoes, Tomatoes, Pumpkin, Winter Melon, Cucumber, Bean Sprouts, Corn, Beans, Radish, Water Spinach, Lotus Root, Celery, Pepper, Wild Rice Stem	84	14,297
Meat&Eggs	Beef, Chicken, Pork, Eggs, Chicken Wings, Chicken Breasts, Chicken Legs, Ribs, Beef Shanks	74	13,738
Aquatic Products	Grass Carp, Carp, Silver Carp, Salmon, Sea Bass, Yellow Croaker, Cuttlefish, Squid, Crab, Shrimp, Lobster, Crayfish, Clam, Loach, Bullfrog	79	14,271
Total		311	56,765

In the fruits category, a diverse selection of 74 products such as grapes, bananas, apples, oranges, pears, and exotic options like dragon fruit, mangosteen, and jackfruit, received a total of 14,459 customer comments. The vegetables category boasts 84 products, including staples like green vegetables, potatoes, tomatoes, and pumpkins, along with more unique options like water spinach, lotus root, and wild rice stem. These products garnered a total of 14,297 customer reviews. The meat & eggs category comprises 74 products, ranging from beef, chicken, and pork to various cuts like chicken breasts, legs, and ribs, as well as

eggs. This category received 13,738 customer comments. The aquatic products category comprises 79 products, including a range of fish such as grass carp, salmon, and sea bass, as well as shellfish and other aquatic delicacies like crab, shrimp, lobster, and crayfish. In total, this category received 14,271 customer reviews.

4.3 Topic Extraction and Validation

This section distills raw customer reviews into 18 validated topics, confirms their coherence, distinctiveness, and stability, maps them to service-quality dimensions and outcome constructs, and verifies both topic and sentiment assignments against a gold-standard sample.

4.3.1 Topic Modeling Outputs

This study employed BERTopic as the primary method for uncovering latent themes in user-generated content. In the initial stage, HDBSCAN clustering automatically identified a set of preliminary topics within the embedding space, thereby capturing the underlying semantic patterns of the corpus. These preliminary clusters were subsequently refined through the class-based TF-IDF (c-TF-IDF) procedure, which merged semantically overlapping or highly similar topics into more coherent groups. To validate the robustness of the modeling outcome, multiple rounds of refinement and resampling were carried out, ensuring that the discovered structures remained consistent across different data partitions. After this process, the final model produced 18 distinct topics, each characterized by interpretability, clear thematic boundaries, and reproducibility.

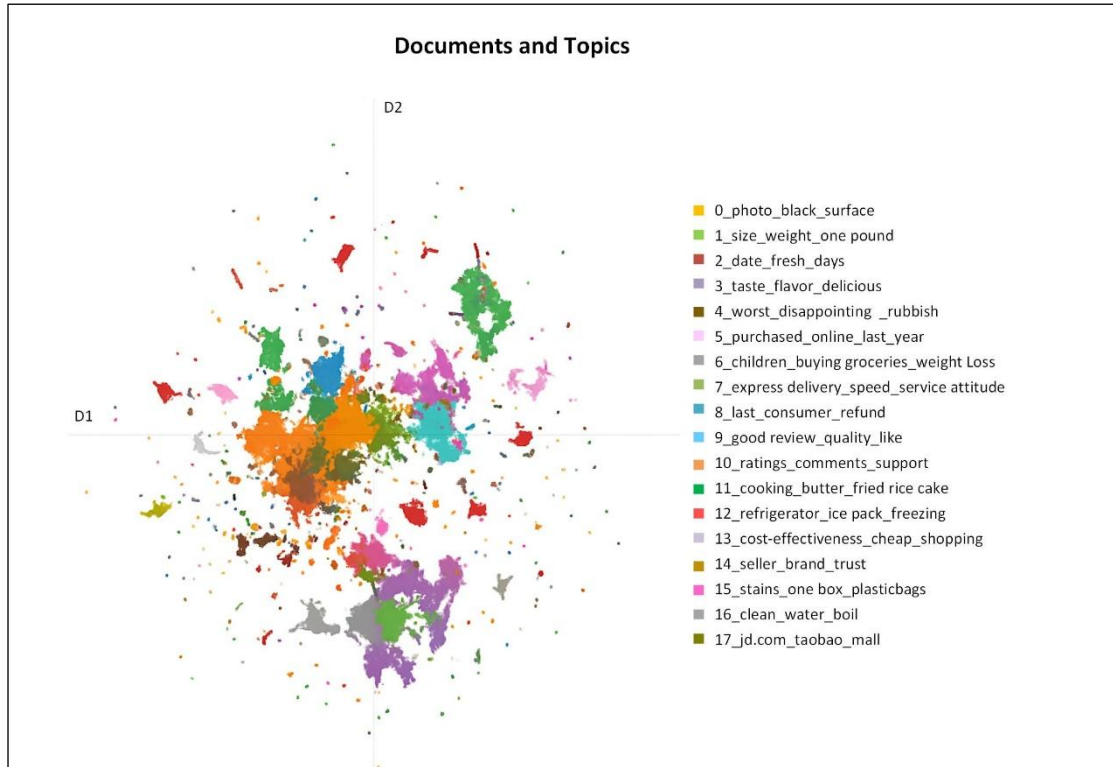


Figure 4.1: Visualization of BERTopic Clustering Results

Figure 4.1 presents the results of topic analysis conducted on a collection of customer reviews. The two-dimensional space (D1 and D2) in the figure is derived from mapping high-dimensional BERT embeddings onto a two-dimensional plane through dimensionality reduction techniques. Each point represents an individual review document, and its location reflects the document's similarity within the topic space. Points of different colors denote distinct topics. The legend on the right side of the figure lists the topic numbers corresponding to each color, along with their descriptions. The points in the figure are clustered based on their similarity within the topic space, forming various clusters. Each cluster represents a group of documents that are thematically similar in content, sharing common topical characteristics.

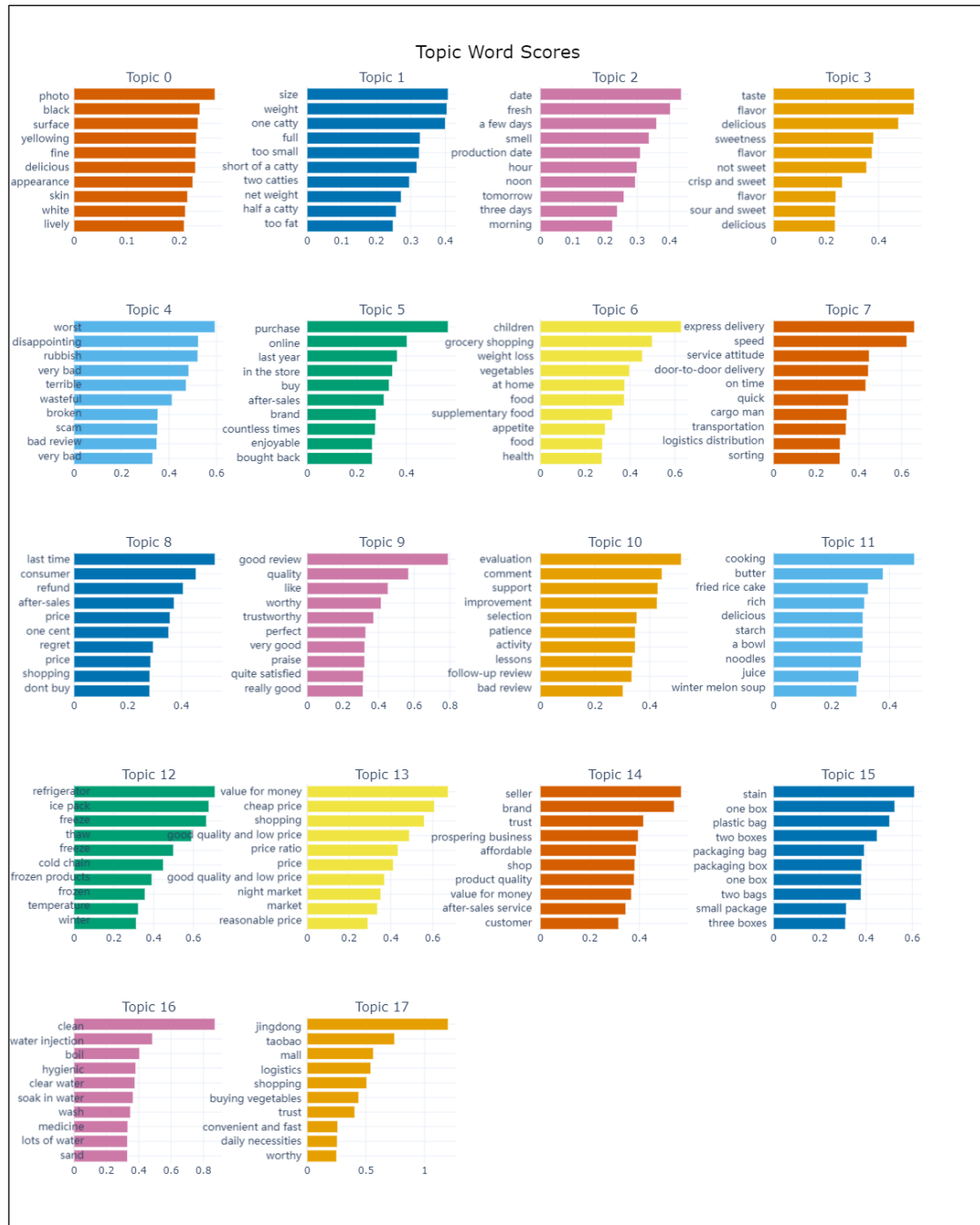


Figure 4.2: Topic Word Scores from Bertopic

Figure 4.2 illustrates the outcomes of applying the Bertopic method to analyze a collection of customer reviews. This visualization technique transforms the high-dimensional representation of text data into a comprehensible format by identifying

dominant themes and associating them with relevant keywords. Each section within the figure corresponds to a unique topic that the Bertopic model has extracted from the dataset.

Figure 4.2 is segmented into distinct topics, labeled from 0 to 17, reflecting the diversity of discussions in the customer reviews. Within each topic section, horizontal bars represent individual words, with the length of each bar indicating the word's relevance score to that particular topic. A longer bar signifies a higher relevance score, denoting greater importance or frequency of the word within the topic. Each topic is assigned a unique color for clear differentiation.

Table 4.2 presents the comprehensive outcomes of topic analysis conducted on review text data utilizing the Bertopic model. Each topic is assigned a unique identifier, ranging from 0 to 17, representing the distinct themes. 'Count' denotes the number of documents affiliated with each topic, reflecting the prevalence of that topic within the dataset. 'Name' provides the designated name for each topic, which encapsulates the essence of the theme. 'Representation' lists the representative keywords for each topic. These terms carry the highest weight within their respective topics and effectively summarize the core content of the theme.

To ensure that the outputs of BERTopic align with the real-world perceptions of consumers and to enhance the interpretability of the model, this study provides a consumer-oriented semantic interpretation for the 18 extracted topics based on their most representative keywords and the review contexts in which they appear.

Table 4.2: Topic Modeling Outputs

Topic	Count	Name	Representation
0	21950	0_photo_black_surface_yellowed	['photo', 'black', 'surface', 'yellowing', 'fine', 'delicious', 'appearance', 'skin', 'white', 'lively']
1	20048	1_size_weight_one pound_full	['size', 'weight', 'one catty', 'full', 'too small', 'short of a catty', 'two catties', 'net weight', 'half a catty', 'too fat']
2	14651	2_date_fresh_days_smell	['date', 'fresh', 'a few days', 'smell', 'production date', 'hour', 'noon', 'tomorrow', 'three days', 'morning']
3	11976	3_taste_flavor_delicious_sweetness	['taste', 'flavor', 'delicious', 'sweetness', 'flavor', 'not sweet', 'crisp and sweet', 'flavor', 'sour and sweet', 'delicious']
4	6240	4_worst_disappointing_rubbish_terrible	['worst', 'disappointing', 'rubbish', 'very bad', 'terrible', 'wasteful', 'broken', 'scam', 'bad review', 'very bad']
5	5681	5_purchased_online_last_year_in-store	['purchase', 'online', 'last year', 'in the store', 'buy', 'after-sales', 'brand', 'countless times', 'enjoyable', 'bought back']
6	5673	6_children_buying groceries_weight loss_vegetables	['children', 'grocery shopping', 'weight loss', 'vegetables', 'at home', 'food', 'supplementary food', 'appetite', 'food', 'health']
7	4893	7_express delivery_speed_service attitude_door-to-door delivery	['express delivery', 'speed', 'service attitude', 'door-to-door delivery', 'on time', 'quick', 'cargo man', 'transportation', 'logistics distribution', 'sorting']
8	4872	8_last_consumer_refund_after-sales	['last time', 'consumer', 'refund', 'after-sales', 'price reduction', 'one cent', 'regret', 'price', 'shopping', 'don't buy']
9	4855	9_good review_quality_like_worthy	['good review', 'quality', 'like', 'worthy', 'trustworthy', 'perfect', 'very good', 'praise', 'quite satisfied', 'really good']
10	4850	10_ratings_comments_support_improvements	['evaluation', 'comment', 'support', 'improvement', 'selection', 'patience', 'activity', 'lessons', 'follow-up review', 'bad review']
11	4399	11_cooking_butter_fried rice cake_rich	['cooking', 'butter', 'fried rice cake', 'rich', 'delicious', 'starch', 'a bowl', 'noodles', 'juice', 'winter melon soup']

Table 4.2 continued

12	4247	12_refrigerator_ice pack_freezing_thawing	['refrigerator', 'ice pack', 'freeze', 'thaw', 'freeze', 'cold chain', 'frozen products', 'frozen', 'temperature', 'winter']
13	4155	13_cost- effectiveness_cheap_sho pping_good quality and low price	['value for money', 'cheap price', 'shopping', 'good quality and low price', 'price ratio', 'price', 'good quality and low price', 'night market', 'market', 'reasonable price']
14	4073	14_seller_brand_trust_pr osperous business	['seller', 'brand', 'trust', 'prospering business', 'affordable', 'shop', 'product quality', 'value for money', 'after-sales service', 'customer']
15	3935	15_stains_one box_plastic bags_two boxes	['stain', 'one box', 'plastic bag', 'two boxes', 'packaging bag', 'packaging box', 'one box', 'two bags', 'small package', 'three boxes']
16	3082	16_clean_water_boil_hy gienic	['clean', 'water injection', 'boil', 'hygienic', 'clear water', 'soak in water', 'wash', 'medicine', 'lots of water', 'sand']
17	1536	17_jd.com_taobao_mall _logistics	['jingdong', 'taobao', 'mall', 'logistics', 'shopping', 'buying vegetables', 'trust', 'convenient and fast', 'daily necessities', 'worthy']

Note: Table 4.2 reports the raw topic-model outputs (topic IDs, counts, and keyword representations) as produced by the algorithm.

T0 concerns product appearance and peel condition; T1 focuses on accuracy of weight and size; T2 reflects freshness and production date; T3 relates to taste and sweetness level; T4 captures complaints and negative appraisals; T5 expresses repurchase intention; T6 conveys family/children happiness and peace of mind; T7 addresses delivery speed, punctuality, and courier attitude; T8 covers refunds, price protection, and after-sales handling; T9 denotes positive appraisals and compliments; T10 involves recommendations and word-of-mouth; T11 describes shopping convenience and cooking ease; T12 highlights cold-chain integrity and temperature control; T13 emphasizes value for money and the price–quality ratio; T14 reflects service attitude and merchant trust; T15 concerns packaging

integrity; T16 relates to clean handling and hygiene; and T17 focuses on platform or mall convenience and navigation experience.

4.3.2 Validation Results of Topic Modeling

For each topic, c-TF-IDF ranks terms by importance, and the top 10 keywords are retained. Per-topic coherence is then computed with Gensim’s C_v (NPMI + sliding window), and summary statistics (mean, SD, min/max) are reported; a PMI-based coherence variant is used to verify that configuration rankings are stable. Topic diversity is calculated as the number of unique words among all topics’ top-10 lists divided by $K \times 10$. For stability, three independent runs are produced (two seeds + one 80% bootstrap). Topics are aligned across runs using maximum-weight bipartite matching on pairwise Jaccard similarity; the average Jaccard of the aligned topics’ unordered top-10 sets summarizes word-level stability. ARI is computed on hard document assignments (highest-scoring topic) to quantify between-run agreement after correcting for chance. The largest difference in the runs’ mean C_v yields $\Delta \overline{C_v}$.

Semantic coherence (C_v) is 0.56 (SD = 0.05; range 0.45–0.68), exceeding the conventional acceptability threshold of 0.45. A PMI-based coherence variant yields the same configuration ranking, indicating that conclusions are not sensitive to the choice of coherence metric. Topic diversity equals 0.90, implying low redundancy of salient vocabulary across topics and well-delineated thematic boundaries; paired with the observed C_v distribution, this suggests adequate interpretability without over-fragmentation.

Regarding stability across reruns, the change in mean coherence is $\Delta \overline{C_v} = 0.012$ (≤ 0.02); after aligning topics across runs, the average Jaccard similarity of unordered top-10

keyword sets is 0.66 (≥ 0.60); at the document level, the Adjusted Rand Index (ARI) based on hard assignments is 0.57 (≥ 0.50). Collectively, these diagnostics support the selected configuration as interpretable, distinctive, and reproducible, providing a reliable basis for indicator construction and subsequent measurement and structural equation modeling (see Table 4.3).

Table 4.3: Diagnostics for Topic Model Selection and Robustness

Metric	Definition / Computation	Value	Criterion
Mean $C_v \pm \text{SD}$	Per-topic c_v (NPMI + sliding window) on top-10 keywords; mean and SD across topics; PMI-based coherence used to cross-check rankings	0.56 ± 0.05	≥ 0.45
Min / Max C_v	Extremes across topics	0.45 / 0.68	—
Topic Diversity	Unique words across all top-10 lists $\div (K \times 10)$	0.90	≈ 0.90 (low redundancy)
ΔC_v (mean)	Max difference of mean C_v across three runs (two seeds + one 80% bootstrap)	0.012	≤ 0.02
Avg Jaccard	Word-level stability: average Jaccard of unordered top-10 sets after topic alignment	0.66	≥ 0.60
ARI	Document-level stability: Adjusted Rand Index on hard assignments (pairwise between runs)	0.57	≥ 0.50

4.3.3 Topic-to-Dimension Mapping

Table 4.2 presents the model's raw output (topic IDs, counts, and keyword representations) prior to any researcher-driven labeling or theoretical categorization. To convert algorithmic topics into constructs suitable for measurement and testing, this subsection specifies the topic-to-dimension mapping procedure and, on that basis, operationalizes each dimension as an observed indicator in Table 4.4 (A1–R4). Variables S4 (star rating), R3 (membership status), and R4 (number of purchases) are behavioral variables rather than topic-derived measures and are included as covariates in modeling.

The mapping draws on three types of evidence for each topic: its c-TF-IDF keywords, three highest-membership representative review excerpts (anonymized), and frequent bigrams in the corpus. Using these materials, a concise customer-language label is assigned to each topic so that the object and focus of evaluation are explicit, and alignment is made to the service-quality dimensions defined in Chapter 2.

Operational definitions and boundary rules are as follows: Fulfillment concerns judgments of the received item's conformity to the order, including quantity/weight/size, taste, freshness, appearance, and condition upon arrival; Logistics Service Quality concerns the delivery process and handling, including timeliness, courier attitude, cold-chain/temperature control, and packaging protection; Customer Service concerns post-purchase support and merchant responsiveness, such as refunds, price protection, and service attitude/trust; Ease of Use concerns shopping and handling convenience and platform usability, including search, ordering, navigation, and cleaning/prep/cooking; Economic Efficiency concerns value-for-money and price fairness; Customer Satisfaction and Repurchase Intention are outcome constructs rather than service-quality dimensions.

Table 4.4: Description of Each Variable

Dimension	Topic	Variable Symbols	Variable Description
Fulfillment	T0	A1	Appearance/peel
	T2	A2	Freshness & production date
	T1	A3	Weight/size accuracy
	T3	A4	Taste and sweetness level
Ease of Use	T11	B1	Shopping effort & cooking convenience
	T16	B2	Clean handling and hygiene
	T17	B3	Platform/mall convenience & navigation
Customer Service	T8	C1	Refunds, price-protection, and after-sales handling
	T14	C2	Service attitude and merchant trust
Logistics Service Quality	T7	D1	Delivery speed, on-time performance, and courier attitude
	T12	D2	Cold-chain integrity/temperature control
	T15	D3	Packaging integrity
Economic Efficiency	T13	E1	Value for money (price–quality ratio)
Customer Satisfaction	T9	S1	Positive appraisal/compliments
	T4	S2	Complaints / negative appraisal
	T6	S3	Family/children happiness & peace-of-mind
	Rating	S4	Star rating (1–5)
Repurchase Intention	T5	R1	Repurchase intention / will buy again
	T10	R2	Recommendation/word-of-mouth
	Membership Status	R3	Membership status (0/1)
	Number of Purchases	R4	Number of purchases

In practical assignment, evaluations of the received product (e.g., underweight/not sweet/yellowing/off-odor) are mapped to Fulfillment; evaluations of the delivery journey (e.g., delays, melted ice packs, crushed cartons, courier attitude) are mapped to Logistics Service Quality; interface/navigation/effort map to Ease of Use; refunds/service

attitude/trust map to Customer Service; “worth it”/value language maps to Economic Efficiency. When mixed cues occur, assignment follows the dominant object referenced by the majority of representative excerpts.

To assess consistency of interpretation, two coders independently applied the same codebook. Dual independent coding yielded an observed agreement (P_o) of 0.89 and an expected agreement (P_e) of 0.32, resulting in Cohen’s $\kappa = 0.84$ (95% CI: 0.56–1.00, $p < 0.001$), indicating substantial agreement ($\kappa \geq 0.70$) (Cohen, 1960; Landis & Koch, 1977). Disagreements were resolved by discussion, and a final mapping was fixed thereafter.

Under these rules, the following correspondences are established and used to set indicator codes in Table 4.4: Fulfillment comprises T0 (appearance/peel) $\rightarrow$ A1, T2 (freshness/production date) $\rightarrow$ A2, T1 (weight/size accuracy) $\rightarrow$ A3, and T3 (taste/sweetness) $\rightarrow$ A4; Ease of Use comprises T11 (prep/cooking convenience) $\rightarrow$ B1, T16 (cleaning/hygiene) $\rightarrow$ B2, and T17 (platform/mall convenience and navigation) $\rightarrow$ B3; Customer Service comprises T8 (refunds/price protection/after-sales handling) $\rightarrow$ C1 and T14 (service attitude/merchant trust) $\rightarrow$ C2; Logistics Service Quality comprises T7 (delivery speed/on-time performance/courier attitude) $\rightarrow$ D1, T12 (cold-chain integrity/temperature control) $\rightarrow$ D2, and T15 (packaging integrity) $\rightarrow$ D3; Economic Efficiency comprises T13 (value-for-money/price–quality trade-off) $\rightarrow$ E1. Outcome constructs are represented as follows: Customer Satisfaction by T9 (positive appraisal) $\rightarrow$ S1, T4 (complaints/negative appraisal) $\rightarrow$ S2, and T6 (family/children happiness and peace-of-mind) $\rightarrow$ S3, supplemented by S4 (star rating); Repurchase Intention by T5 (repeat purchase/will buy again) $\rightarrow$ R1 and T10 (recommendation/word-of-mouth) $\rightarrow$ R2,

supplemented by R3 (membership status) and R4 (number of purchases). Through this mapping, service-quality dimensions and outcome constructs are operationalized as measurable indicators grounded in customer language.

4.3.4 Validation Results of Sentiment Analysis

A gold-standard sample ($n = 180$), selected randomly based on topic, platform, and product category, was used to evaluate two tasks: clause-to-topic assignment and clause-level sentiment classification. Using a predetermined codebook, two trained annotators independently and blindly labeled each clause with a single “best” topic and a sentiment label (negative/neutral/positive). Inter-annotator agreement was measured with Cohen’s κ (target $\kappa \geq 0.70$); disagreements were resolved through adjudication to establish the gold standard. The system was then evaluated against this reference using Top-1 accuracy; for sentiment, precision, recall, and F1-score were also provided for each class.

For the topic assignment, the overall Top-1 accuracy was 0.80 (95% CI: 0.74–0.86). Per-topic F1 (Table 4.5) ranged from 0.67 to 0.81, showing manageable variability.

Table 4.5: Topic Assignment Metrics

Topic	Precision	Recall	F1
T0	0.74	0.76	0.75
T1	0.70	0.72	0.71
T2	0.75	0.71	0.73
T3	0.78	0.79	0.79
T4	0.68	0.66	0.67
T5	0.73	0.70	0.71

Table 4.5 continued

T6	0.71	0.74	0.72
T7	0.77	0.78	0.78
T8	0.69	0.68	0.68
T9	0.76	0.75	0.75
T10	0.70	0.69	0.69
T11	0.74	0.72	0.73
T12	0.79	0.80	0.79
T13	0.72	0.73	0.73
T14	0.73	0.74	0.73
T15	0.75	0.71	0.73
T16	0.71	0.70	0.71
T17	0.80	0.82	0.81

For sentiment classification (Table 4.6), overall accuracy was 0.84 (95% CI: 0.79–0.89); class-wise precision, recall, and F1 scores show approximately balanced performance at or above the predefined thresholds.

Table 4.6: Sentiment Classification Metrics

Class	Precision	Recall	F1
Negative	0.77	0.73	0.75
Neutral	0.75	0.78	0.76
Positive	0.83	0.81	0.82

Annotator reliability reached $\kappa = 0.72$ for topic assignment and $\kappa = 0.76$ for sentiment, corresponding to substantial agreement, with percent agreement of 0.86 and 0.88, respectively. These results indicate that the gold standard is dependable for evaluation and calibration.

4.4 Descriptive Statistical Analysis

To comprehensively evaluate the emotional tendencies of customer feedback across various thematic dimensions, this study utilized the Baidu Text Sentiment Analysis API to compute sentiment scores for each comment, as outlined in Chapter 3. Since individual comments usually cover only a subset of themes rather than the entire range, a direct analysis of the sentiment scores of individual comments could result in biased findings. Consequently, this study implemented an aggregation process for the comment data: initially, comments were grouped by product, and then the sentiment scores of all pertinent comments for each product were averaged across the thematic dimensions to produce a more comprehensive and representative assessment of product sentiment. Ultimately, through this aggregation approach, the study secured an analytical sample consisting of 311 data entries, each containing the average sentiment scores for the respective product across diverse thematic dimensions.

To scrutinize the distribution of sample scores and their conformity to the normal distribution in depth, this study employed SPSS 27.0 to perform a thorough descriptive statistical analysis on each variable. This analysis framework encompasses the extreme values (maximum and minimum), central tendency (mean), dispersion (standard deviation) of each item score, as well as crucial indicators of distribution shape - skewness and kurtosis.

Table 4.7: Descriptive Statistical Analysis

Variable	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
A1	-0.975929	0.926946	-0.013031	0.478266	0.074	-1.071
A2	-0.989815	0.721006	-0.103875	0.378535	0.228	-0.774
A3	-0.960578	0.884875	0.183878	0.364824	-0.221	-0.338
A4	-0.999839	0.998076	0.301935	0.483420	-0.577	-0.377
B1	-0.998697	0.999989	0.325608	0.475516	-0.651	-0.113
B2	-0.999699	0.999554	-0.059127	0.569152	0.082	-0.929
B3	-0.998134	0.999880	0.162447	0.453283	0.169	0.547
C1	-0.999947	0.998434	-0.605293	0.397337	1.856	4.149
C2	-0.999983	0.999946	0.203302	0.639401	-0.510	-0.776
D1	-0.999995	0.999848	0.565880	0.505774	-1.554	1.892
D2	-0.999795	0.999204	-0.075647	0.519154	0.266	-0.324
D3	-0.997860	0.999616	0.366759	0.518564	-0.874	0.047
E1	-0.999939	0.999575	0.522221	0.501030	-1.523	1.804
S1	0.000000	0.959588	0.219380	0.151653	1.092	1.337
S2	-0.999976	0.635121	-0.743958	0.332654	1.798	2.764
S3	-0.999966	0.999871	0.232025	0.670743	-0.423	-1.018
S4	1.517241	4.983730	3.533944	0.823033	0.006	-0.777
R1	-0.999836	0.999720	0.531048	0.448744	-1.440	2.196
R2	-0.999854	0.998875	0.295114	0.558590	-0.739	-0.303
R3	0.038462	1.000000	0.828528	0.218146	-0.845	-0.372
R4	1.000000	7.881101	2.357192	1.392536	1.307	1.168

Variables such as A, B, C, D, E, S1, S2, S3, R1, and R2 all stem from the outcomes of topic modeling and sentiment analysis, with their score range restricted to -1 to 1. Additionally, S4 signifies the star rating of reviews aggregated by product, spanning from 1 to 5; R3 denotes the membership score, which ranges between 0 and 1 after aggregation by product; and R4 documents the number of purchases, with a minimum value of 1.

In assessing the normality of the sample data, this study adhered to the prevalent practice in academia, namely, making judgments by examining the skewness and kurtosis coefficients. Typically, when the skewness coefficient is less than 3 and the kurtosis coefficient is less than 8, it can be tentatively assumed that the data approximates a normal distribution. The data presented in Table 4.7 reveal that the skewness coefficients of all items are less than 2, and the kurtosis coefficients are less than 5. This outcome is markedly better than the aforementioned standards, confirming that the sample data in this study follows a normal distribution.

Outlier screening of the 311 product-level observations identified seven univariate cases with $|z| > 3.29$ and three multivariate cases with Mahalanobis $D^2 > 46.8$ ($\chi^2_{0.991, df = 21}$). Manual review reclassified four as text-processing errors and corrected them; the remaining six were retained as genuine extreme reviews. No cases were removed, leaving the final sample intact at $n = 311$.

4.5 Correlation Analysis

To explore the potential correlation among different variable dimensions, this research utilizes SPSS 27.0 to conduct Pearson correlation analysis on each dimension of the variables. Since these variables are all grounded in high-level constructs, their specific

values are derived by summing the scores of each dimension and then calculating the average.

Table 4.8 provides a detailed listing of the correlation coefficients between the variables.

Table 4.8: Correlation Matrix

	Fulfill	EU	CSE	LSQ	EE	CS	RI
Fulfill	1						
EU	.311	1					
CSE	.391	.227	1				
LSQ	.356	.199	.302	1			
EE	.425	.330	.344	.294	1		
CS	.514	.412	.527	.410	.547	1	
RI	.466	.309	.448	.383	.465	.589	1

Note: Correlation is significant at the 0.01 level (two-tailed). Fulfill: Fulfillment, EU: Ease of Use, CSE: Customer Service, LSQ: Logistics Service Quality, EE: Economic Efficiency, CS: Customer Satisfaction, RI: Repurchase Intention.

Table 4.9: Variance Inflation Factors for Predictor Constructs

Variable	VIF
Fulfillment	1.43
Ease of Use	1.18
Customer Service	1.27
Logistics Service Quality	1.21
Economic Efficiency	1.36

From the data presented in Table 4.8, it is clear that there is a significant correlation among the dimensions of each variable. At the same time, all Pearson correlation coefficients remain below 0.8, which indicates that there is no multicollinearity problem among the dimensions of each variable. Therefore, the next step of data analysis can be carried out.

In addition, to further assess multicollinearity at the construct level, Variance Inflation Factors (VIF) were calculated for all predictor constructs, as shown in Table 4.9. The results showed that all VIF values were below the conservative threshold of 3.3 (Sarstedt, 2019), indicating the absence of multicollinearity issues.

4.6 Confirmatory Factor Analysis

Before estimating the structural model, Confirmatory Factor Analysis (CFA) was conducted to assess the reliability, convergent validity, and discriminant validity of the six multi-item constructs, excluding Economic Efficiency. The sample size was $N = 311$, and maximum likelihood (ML) estimation was employed. Model specification was as follows: Each observed indicator was allowed to load on its designated latent factor only. Latent factors were permitted to correlate freely. Economic Efficiency, a single-indicator construct, was handled by fixing its factor loading to 1 and its error variance to 0; consequently, it was excluded from reliability and validity assessments.

Table 4.10 provides a detailed summary of the standardized factor loadings, Cronbach's α coefficients, composite reliability (CR), and average variance extracted (AVE) for all constructs included in the measurement model. All factor loadings are statistically significant at $p < 0.001$, confirming that the observed items strongly reflect their respective latent constructs. The Cronbach's α values range from 0.81 to 0.90, the CR values from 0.82 to 0.91, and the AVE values from 0.58 to 0.77, all exceeding commonly recommended thresholds.

Table 4.10: Measurement Model Reliability and Convergent Validity

Construct / Item	Std. Loading	Cronbach's α	CR	AVE
Fulfillment		0.84	0.84	0.64
A1	0.95***			
A2	0.87***			
A3	0.68***			
Ease of Use		0.83	0.86	0.67
B1	0.80***			
B2	0.87***			
B3	0.76***			
Customer Service		0.81	0.82	0.70
C1	0.76***			
C2	0.88***			
Logistics Service		0.83	0.85	0.66
D1	0.76***			
D2	0.71***			
D3	0.83***			
Customer Satisfaction		0.89	0.91	0.71
S1	0.79***			
S2	0.83***			
S3	0.85***			
S4	0.81***			
Repurchase Intention		0.89	0.90	0.75
R1	0.85***			
R2	0.90***			
R3	0.88***			
R4	0.86***			

Note: *** $p < 0.001$.

Discriminant validity was assessed using the Fornell–Larcker criterion. As shown in Table 4.11, the square root of AVE (bold on the diagonal) for each construct exceeds its highest correlation with any other construct, confirming adequate discriminant validity.

Table 4.11: Discriminant Validity (AVE Square Root and Factor Correlations)

Variable	Fulfill	EU	CSE	LSQ	CS	RI
Fulfill	0.80					
EU	0.45	0.82				
CSE	0.39	0.36	0.84			
LSQ	0.52	0.48	0.42	0.81		
CS	0.58	0.55	0.49	0.61	0.84	
RI	0.62	0.59	0.51	0.64	0.76	0.87

Note: Fulfill: Fulfillment, EU: Ease of Use, CSE: Customer Service, LSQ: Logistics Service Quality, EE: Economic Efficiency, CS: Customer Satisfaction, RI: Repurchase Intention.

The CFA model exhibited satisfactory fit: CMIN/DF = 2.31, GFI = 0.92, NFI = 0.94, CFI = 0.960, TLI = 0.950, RMSEA = 0.065 (90% CI: 0.056–0.074). All indices meet or exceed the recommended thresholds (Hu & Bentler, 1998). Therefore, the measurement model demonstrates adequate reliability and validity and can be used for the subsequent structural model analysis.

4.7 Structural Equation Modeling

When researchers find themselves deeply engaged in the intricate task of exploring the complex causal relationships that exist between multiple independent variables and dependent variables, structural equation modeling (SEM) emerges as an exceptionally advantageous and highly appropriate method (Byrne, 2010).

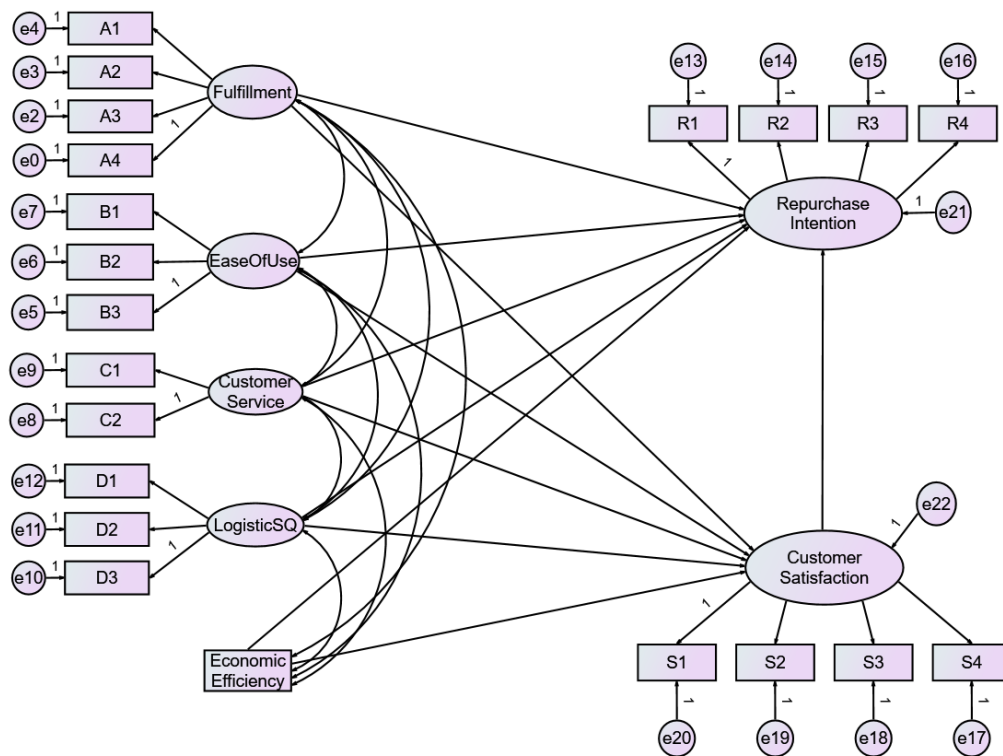


Figure 4.3: Structural Equation Modeling Diagram

SEM allows for the simultaneous examination of multiple relationships, providing a comprehensive understanding of how various factors interact. The model paths are specified according to the research framework depicted in Figure 2.4 and hypotheses H1–H12. Based on the research hypothesis outlined in Chapter 2, a structural equation model was constructed using AMOS 26.0. This model, depicted in Figure 4.3, embodies the theoretical framework of the study, illustrating the hypothesized pathways and interactions among the variables of interest. By employing this model, the aim is to test and validate the hypotheses, thereby shedding light on the underlying mechanisms that drive the relationships under investigation.

In structural equation modeling (SEM), model fit assesses how well the hypothesized structure reproduces the observed variance and covariance matrix. The chi-square divided by degrees of freedom (CMIN/DF or CMIN/DF) summarizes residual misfit per parameter;

smaller values indicate better fit, with values below 3 considered ideal and below 5 acceptable. The Goodness of Fit Index (GFI) is an absolute fit measure that shows the proportion of variance and covariance explained; values of at least 0.90 indicate good fit. The Normed Fit Index (NFI) compares the target model to a null independence model; values of at least 0.90 show significant improvement. The Comparative Fit Index (CFI) also benchmarks against the null model while reducing bias in small samples; values of at least 0.90, and often 0.95 for excellent fit, suggest good fit. The Tucker–Lewis Index (TLI, also NNFI) accounts for model complexity; values of at least 0.90 indicate good and parsimonious fit. The Root Mean Square Error of Approximation (RMSEA) estimates discrepancy in the population per degree of freedom; values at or below 0.05 suggest close fit, and those at or below 0.08 indicate reasonable fit. These interpretations align with the threshold ranges reported in Table 4.12.

Table 4.12: Evaluation Metrics for Model Fit

Indicator	Standard Value Range
CMIN/DF	< 3(ideal), < 5(acceptable)
GFI	≥ 0.9
NFI	≥ 0.9
CFI	≥ 0.9
TLI	≥ 0.9
RMSEA	≤ 0.05 (ideal), ≤ 0.08 (good)

Source: Principles and practice of structural equation modeling (Kline, 2023a)

To boost the credibility of subsequent analysis, the first step before validating the theoretical model is to evaluate the goodness of fit of the constructed structural equation model, with the goal of providing stronger support for the hypotheses presented in this thesis.

Calculations have been used to obtain the goodness-of-fit indices, which are shown in Table 4.13.

Table 4.13: Test Results of Model Fit Indices

Indicator	CMIN/DF	GFI	NFI	CFI	TLI	RMSEA
Test Result	2.857	0.869	0.880	0.918	0.899	0.077
Fitting Effect	Ideal	Acceptable	Acceptable	Ideal	Acceptable	Good

Chi-square quantifies the goodness of fit between structural equation models and sample data. At the same time, the degree of freedom represents the amount of information in the sample that can be independently varied when estimating population parameters. In structural equation modeling, a smaller chi-square value is ideal, indicating a closer fit. Conversely, a higher degree of freedom generally signifies greater reliability. Given that chi-square statistics vary with sample size, the CMIN/DF ratio (chi-square value divided by degrees of freedom) is used to more precisely assess the fit. This ratio indicates how closely the sample covariance matrix aligns with the estimated variance matrix, serving as a crucial metric. Specifically, a CMIN/DF value closer to 0 reflects better model fit. A ratio below 3 is generally deemed satisfactory, while a ratio between 3 and 5 is considered acceptable but not optimal. In this study, the CMIN/DF ratio was 2.857, indicating good model fit.

The Goodness of Fit Index (GFI), or Adjusted GFI, ranges from 0 to 1. A GFI closer to 1 signifies better fit, while a GFI closer to 0 indicates poorer fit. A GFI above 0.9 is generally considered excellent, and between 0.7 and 0.9 is acceptable. In this study, the initial GFI was 0.869, which is acceptable but can be improved. Through adjustments, the model's fit is expected to enhance.

The Normalized Fit Index (NFI) and Comparative Fit Index (CFI) are widely recognized indicators for evaluating model fit, with similar evaluation criteria to GFI. Values above 0.9 are considered excellent, and between 0.7 and 0.9 are acceptable. In this study, the NFI was 0.880 and the CFI was 0.918, both within the acceptable range.

RMSEA (Root Mean Square Error of Approximation) measures model error size. A value closer to 0 indicates better fit. Generally, RMSEA below 0.05 is very good, 0.05 to 0.08 is acceptable, and 0.08 to 0.1 is average. In this study, the RMSEA was 0.077, which is acceptable.

Through analysis of the model fitting indicators, the initial model has room for improvement. Adjustments were made based on the Modification Indices (MI) from Amos 26.0. The optimized model is shown in Figure 4.4.

The adjusted model was re-evaluated to assess its fitting results. The compiled fitting indicators are presented in Table 4.13. Upon observing the data in Table 4.14, it becomes evident that the adjusted model has shown improvement across all fitting indicators. Specifically, the CMIN/DF value now falls within an acceptable range, indicating a closer alignment between the model and the data. The GFI, NFI, CFI, and TLI have all risen, approaching the thresholds that denote an excellent fit, while the RMSEA value has decreased, further confirming the enhanced fit quality of the model.

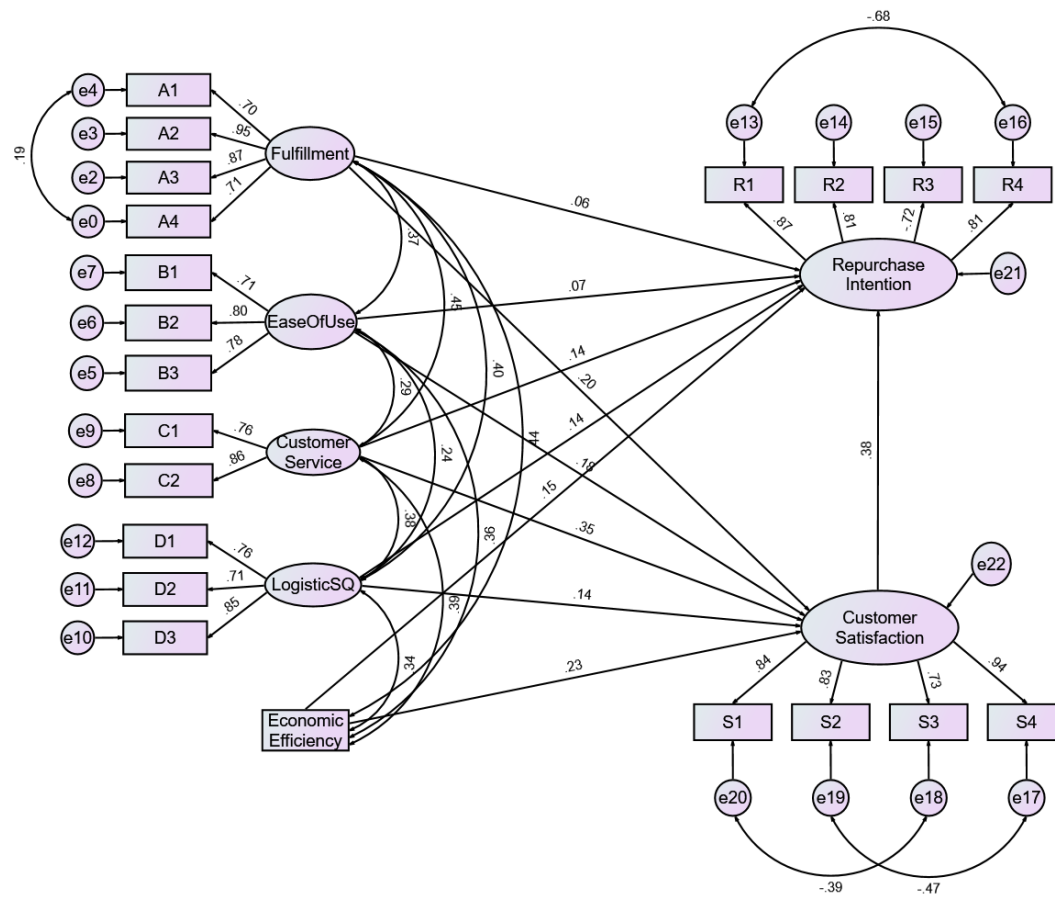


Figure 4.4: Adjusted Structural Equation Model

In the revised model, all reported indices indicate a good overall fit. The CMIN/DF is 2.215, which is below the commonly recommended cutoff of 3 and suggests a satisfactory balance between fit and parsimony. The absolute fit measures GFI = 0.901 and NFI = 0.909 exceed the 0.90 benchmark, indicating adequate reproduction of the observed variance–covariance structure. The incremental fit indices CFI = 0.947 and TLI = 0.933 are both above 0.90, with the CFI approaching the 0.95 level often associated with excellent fit. The RMSEA is 0.063, which is below the generally accepted 0.08 threshold and thus signals a reasonable to good approximation to the population covariance matrix. Overall, these values support the conclusion that the revised model provides a good fit to the data.

Table 4.14: Test Results of the Adjusted Model Fitting Index

Indicator	CMIN/DF	GFI	NFI	CFI	TLI	RMSEA
Adjusted Inspection Results	2.215	0.901	0.909	0.947	0.933	0.063
Inspection Results Before Adjustment	2.857	0.869	0.880	0.918	0.899	0.077
Fitting Effect	Ideal	Ideal	Ideal	Ideal	Ideal	Good

Table 4.15 presents the analysis results for the relationship between two dependent variables, Customer Satisfaction and Repurchase Intention, and five independent variables: Fulfillment, Ease of Use, Customer Service, Logistics Service Quality, and Economic Efficiency. The standardized coefficient estimates, standard errors (S.E.), critical ratios (C.R.), p-values (P), and significance levels for each independent variable are listed. The p-value indicates the probability of obtaining the observed results by chance, while the C.R. represents the strength of the relationship between the independent and dependent variables.

Fulfillment has a significant positive impact on Customer Satisfaction ($p < 0.001$, C.R. = 3.716). Ease of Use also exhibits a significant positive impact on Customer Satisfaction ($p < 0.001$, C.R. = 3.605). Customer Service demonstrates a significant positive impact on Customer Satisfaction ($p < 0.001$, C.R. = 5.863). Logistics Service Quality indicates a significant positive impact on Customer Satisfaction ($p = 0.008$, C.R. = 2.658). Economic Efficiency similarly has a significant positive impact on Customer Satisfaction ($p < 0.001$, C.R. = 4.821). Fulfillment does not have a significant effect on Repurchase Intention ($p = 0.266$, C.R. = 1.112). Ease of Use likewise does not have a significant effect on Repurchase Intention ($p = 0.207$, C.R. = 1.262). However, Customer Service has a significant positive impact on Repurchase Intention ($p = 0.036$, C.R. = 2.091). Logistics

Service Quality also has a significant positive impact on Repurchase Intention ($p = 0.009$, C.R. = 2.595). Economic Efficiency, too, has a significant positive impact on Repurchase Intention ($p = 0.005$, C.R. = 2.798). Lastly, Customer Satisfaction has a significant positive impact on Repurchase Intention ($p < 0.001$, C.R. = 4.853).

Table 4.15: Analysis Results of the Variable Relationships

Hypothesis	Variable Relationship	Estimate	S.E.	C.R.	P	Significance
H1	Customer Satisfaction ← Fulfillment	0.199	0.020	3.716	*	Significant
H2	Customer Satisfaction ← Ease of Use	0.182	0.018	3.605	*	Significant
H3	Customer Satisfaction ← Customer Service	0.355	0.014	5.863	*	Significant
H4	Customer Satisfaction ← Logistics Service Quality	0.135	0.015	2.658	0.008	Significant
H5	Customer Satisfaction ← Economic Efficiency	0.23	0.012	4.821	*	Significant
H6	Repurchase Intention ← Fulfillment	0.063	0.064	1.112	0.266	Not significant
H7	Repurchase Intention ← Ease of Use	0.07	0.061	1.262	0.207	Not significant
H8	Repurchase Intention ← Customer Service	0.14	0.048	2.091	0.036	Significant
H9	Repurchase Intention ← Logistics Service Quality	0.143	0.049	2.595	0.009	Significant
H10	Repurchase Intention ← Economic Efficiency	0.146	0.041	2.798	0.005	Significant
H11	Repurchase Intention ← Customer Satisfaction	0.377	0.239	4.853	*	Significant

Note: Column “H” lists the hypothesis numbers corresponding to each path. * denotes a significance level of 0.001.

4.8 Mediation Effect Test

The bootstrap procedure (5,000 resamples) confirmed partial mediation by Customer Satisfaction (CS) for every antecedent of repurchase intention (RI). As shown in Table 4.16, all five indirect effects are significant at $p < 0.05$, and the 95 % bias-corrected confidence intervals exclude zero, indicating that CS partially transmits the influence of each service-quality dimension to RI.

Table 4.16: Bootstrap Test Results for Customer Satisfaction

Hypothesis	Variable Relationship	Estimate	Lower	Upper	P
H12a	Fulfillment→CS→RI	0.085	0.035	0.162	0.008
H12b	Ease of Use→CS→RI	0.076	0.027	0.141	0.005
H12c	Customer Service→CS→RI	0.096	0.05	0.167	0.005
H12d	Logistics Service Quality→CS→RI	0.045	0.01	0.083	0.017
H12e	Economic Efficiency→CS→RI	0.068	0.034	0.128	0.003

Note: CS: Customer Satisfaction, RI: Repurchase Intention.

For the pathway “Fulfillment → CS → RI”, the estimated coefficient is 0.085, with a 95% confidence interval spanning from 0.035 to 0.162, and a P-value of 0.008. Since the confidence interval excludes zero and the P-value is less than 0.05, it is reasonable to conclude that fulfillment has a significant indirect effect on repurchase intention through customer satisfaction. Specifically, an improvement in fulfillment leads to an average increase of 0.085 units in repurchase intention, mediated by customer satisfaction.

Similarly, for the pathway “Ease of Use → CS → RI”, the estimated coefficient is 0.076, with a 95% confidence interval ranging from 0.027 to 0.141, and a P-value of 0.005. Given that the confidence interval does not contain zero and the P-value is below 0.05, it can

be deduced that ease of use exerts a significant indirect influence on repurchase intention via customer satisfaction. As ease of use improves, the mediating effect of customer satisfaction results in an average increase of 0.076 units in repurchase intention.

For the pathway “Customer Service $\rightarrow$ CS $\rightarrow$ RI”, the estimated coefficient is 0.096, indicating an indirect effect of 0.096 units on repurchase intention through customer satisfaction. The 95% confidence interval extends from 0.05 to 0.167, with a P-value of 0.005, suggesting statistical significance for the mediation effect.

For the pathway “Logistics Service Quality $\rightarrow$ CS $\rightarrow$ RI”, the estimated coefficient is 0.045, reflecting an indirect impact of 0.045 units on repurchase intention mediated by customer satisfaction. The 95% confidence interval lies between 0.01 and 0.083, with a P-value of 0.017, indicating statistical significance for the mediation effect.

For the pathway “Economic Efficiency $\rightarrow$ CS $\rightarrow$ RI”, the estimated coefficient is 0.068, suggesting an indirect effect of 0.068 units on repurchase intention through customer satisfaction. The 95% confidence interval spans from 0.034 to 0.128, with a P-value of 0.003, which confirms the statistical significance of the mediation effect.

4.9 Result of the Hypotheses Testing

As shown in Table 4.17, all five service-quality dimensions significantly improve customer satisfaction, supporting H1 through H5. Concerning direct effects on repurchase intention, customer service, logistics service quality, and economic efficiency are significantly positive (supporting H8–H10). In contrast, the direct effects of fulfillment and ease of use are not significant, so H6 and H7 are not supported. Customer satisfaction has a significant positive impact on repurchase intention, supporting H11.

Table 4.17: Summary of Hypothesis Testing Results

Hypothesis	Hypothesis Testing Results
H1: Fresh e-commerce fulfillment has a significant positive effect on customer satisfaction.	Supported
H2: Fresh e-commerce logistics service quality has a significant positive effect on customer satisfaction.	Supported
H3: Fresh e-commerce ease of use has a significant positive effect on customer satisfaction.	Supported
H4: Fresh e-commerce customer service has a significant positive effect on customer satisfaction.	Supported
H5: Fresh e-commerce economic efficiency has a significant positive effect on customer satisfaction.	Supported
H6: Fresh e-commerce fulfillment has a significant positive effect on repurchase intention.	Not supported
H7: Fresh e-commerce ease of use has a significant positive effect on repurchase intention.	Not supported
H8: Fresh e-commerce customer service has a significant positive effect on repurchase intention.	Supported
H9: Fresh e-commerce logistics service quality has a significant positive effect on repurchase intention.	Supported
H10: Fresh e-commerce economic efficiency has a significant positive effect on repurchase intention.	Supported

Table 4.17 continued

H11: Fresh e-commerce customer satisfaction has a significant positive effect on repurchase intention.	Supported
H12a: Customer satisfaction mediates the relationship between fulfillment and repurchase intention.	Supported
H12b: Customer satisfaction mediates the relationship between logistics service quality and repurchase intention.	Supported
H12c: Customer satisfaction mediates the relationship between ease of use and repurchase intention.	Supported
H12d: Customer satisfaction mediates the relationship between customer service and repurchase intention.	Supported
H12e: Customer satisfaction mediates the relationship between economic efficiency and repurchase intention.	Supported

Bootstrap tests of mediation further indicate that all five indirect effects via customer satisfaction are significant and positive, supporting H12a–H12e: the effects of fulfillment and ease of use on repurchase intention mainly operate through customer satisfaction (full/indirect mediation), while customer service, logistics service quality, and economic efficiency show partial mediation.

4.10 Summary

In summary, this chapter provides a detailed empirical analysis of the relationships among online service quality, customer satisfaction, and repurchase intention in China's fresh e-commerce. The findings confirm that fulfillment, Logistics Service Quality, ease of

use, customer service, and economic efficiency significantly impact customer satisfaction, which in turn positively influences repurchase intention. While fulfillment and ease of use do not directly affect repurchase intention, they indirectly contribute through their impact on customer satisfaction. The mediating role of customer satisfaction is further validated, highlighting its importance in bridging the gap between service quality and repurchase intention. The data presented in this chapter lays a robust foundation for understanding the key factors that influence customer behavior and strategic decision-making in the fresh e-commerce.

CHAPTER 5

DISCUSSIONS, CONCLUSION, AND RECOMMENDATIONS

5.1 Introduction

This chapter presents a comprehensive analysis of the study's findings on service quality in China's fresh e-commerce, examining the critical dimensions that influence customer satisfaction and repurchase intention. Through rigorous statistical analysis and text mining techniques, the research explores the direct and indirect impacts of various service quality factors, including fulfillment, logistics, ease of use, customer service, and economic efficiency. The chapter also discusses the mediating role of customer satisfaction in shaping repurchase intentions, offering valuable insights into how fresh e-commerce platforms can enhance their service offerings to foster customer loyalty. Additionally, it highlights the limitations of the study and suggests avenues for future research, aiming to provide both theoretical contributions and practical guidance for improving customer experience in the fresh e-commerce industry.

5.2 Discussion on Research Findings

This section interprets the empirical results on how dimensions of service quality shape customer satisfaction and repurchase intention in the context of fresh e-commerce. The discussion explicitly relates the evidence to three foundational perspectives, namely Expectation Confirmation Theory, the Stimulus Organism Response model, and Means Ends chain theory.

5.2.1 Research Objective 1: To investigate the impact of service quality towards consumer satisfaction

For the relationship between service quality and satisfaction, fulfillment captures whether goods arrive on time, intact, accurate to description, fresh, and appropriate in weight, size, and experiential attributes such as taste. Satisfaction rises when perceived performance meets or exceeds prior expectations, as posited by Expectation Confirmation Theory (Bhattacharjee, 2001; Oliver, 1980). In the Stimulus Organism Response account, delivery performance operates as an external stimulus that reduces uncertainty and triggers positive internal states that manifest as higher satisfaction (Eroglu et al., 2001; Mehrabian & Russell, 1974). Means Ends chain theory explains the pathway from attributes to consequences to values, where accurate picking, freshness, and integrity of goods deliver consequences such as food safety, good taste, and time savings that realize higher order values of health, family wellbeing, and peace of mind, thereby elevating satisfaction (Reynolds & Gutman, 2001).

Logistics service quality, including delivery speed, reliable time windows, cold chain integrity, and professional packaging, strengthens confirmation, improves internal states such as trust and perceived control, and raises satisfaction within both the Expectation Confirmation and Stimulus Organism Response frameworks (Eroglu et al., 2001; Mehrabian & Russell, 1974; Oliver, 1980). Ease of use contributes to satisfaction by lowering cognitive effort and supporting values related to efficiency and self efficacy, a mechanism consistent with early adoption insights from the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology (Davis, 1989; Venkatesh et al., 2003).

Customer service quality and perceived economic efficiency further raise satisfaction by resolving problems, reducing risk, and delivering value for money, consistent with

research on perceived value and loyalty formation in services and electronic markets (Anderson & Srinivasan, 2003; Zeithaml, 1988).

In the fulfillment dimension, customers are concerned about a comprehensive service quality. This encompasses multiple aspects, ranging from product quality, performance, and description accuracy, to product freshness, appearance vitality, product weight, size accuracy, as well as the final taste and texture. Customers expect the products they receive to not only match the description but also meet their expectations in terms of quality, whether it's durability or functionality. For fresh products, freshness is of particular concern to users, as they directly affect their consumption experience and health. At the same time, the weight and size of the product are also key concerns for users. Finally, customers also pay attention to the taste and texture of the product. Fulfillment has a significant positive impact on customer satisfaction.

Logistics services serve as a pivotal bridge between fresh e-commerce and customers, playing a crucial role in enhancing customer satisfaction and driving sustainable growth for businesses. There is a significant correlation between the logistics service quality of fresh e-commerce and customer satisfaction (Yang et al., 2024). Customers' requirements for the logistics service quality of fresh e-commerce mainly focus on delivery speed, delivery method, delivery time, cold chain technology, and professional packaging. Fresh products are prone to damage or spoilage during the logistics process due to their perishable and perishable characteristics. However, when logistics services can provide fast, timely, and safe delivery, while utilizing advanced methods such as cold chain technology and professional packaging, the quality and freshness of fresh products can be effectively guaranteed. Therefore, it can be said that the quality of logistics services plays a crucial role

in the field of fresh e-commerce, as it directly affects customers' shopping experience and satisfaction.

The comment topics related to "Ease of Use" encompass various aspects, including the smoothness of the shopping process (e.g., Shopping, Strenuous, Suitable, Cooking), ease of operation and hygiene (e.g., Easy, Clean, Sanitary, Well Handled), as well as the convenience and daily usability experience (e.g., Convenient, Mall, Experience, Daily). Ease of Use is directly tied to the user's experience when using a product or service. When the platform's operating interface is user-friendly and the process is straightforward, users can effortlessly complete shopping or operational tasks, minimizing the troubles and frustrations arising from complex operations. This seamless operational experience boosts user satisfaction, as they can efficiently access the necessary information or services. Usability also pertains to users' sense of security and trust in the product or service. For instance, when fresh food e-commerce platforms offer a clean and hygienic shopping environment, along with properly handled goods, users develop a higher level of trust in the platform. When users experience convenience and comfort during the shopping process, they are more inclined to have positive evaluations of the platform or product. Such positive evaluations translate into higher customer satisfaction.

Customer Service has been validated to have a positive impact on customer satisfaction. The comment topics extracted regarding Customer Service include After-sales, Refund, Last time, and Return, as well as Service Attitude, Merchant, Store, Customer, etc. High quality customer service can solve problems encountered by customers during the use of products or services. Whether it's after-sales support, refund processing, or return services, they are all aspects that customers may encounter in their shopping experience. When these

processes are properly handled, customer problems and concerns are resolved, thereby increasing their satisfaction. The service attitude in customer service has a significant impact on customer satisfaction. A friendly and patient service attitude can make customers feel respected and cared for, thereby enhancing their favorability towards the brand or merchant. On the contrary, if the service attitude is poor or impatient, it is easy to cause customer dissatisfaction and complaints.

The research findings support a positive correlation between economic efficiency and customer satisfaction, aligning with numerous research conclusions. When consumers feel that electronic retailers have reasonable pricing and high service quality, they usually feel satisfied (Venkatakrishnan et al., 2023). Customers pay close attention to cost-effectiveness, affordable prices, good quality, and low prices and price ratios when evaluating economic benefits. Reasonable pricing ensures that customers do not feel overcharged, while high-quality service reassures them that they get value for their money. When these two elements are combined, it creates a positive perception of the enterprise in the minds of consumers.

5.2.2 Research Objective 2: To examine the impact of service quality towards consumer repurchase intention

Regarding direct effects on repurchase intention, the results show that fulfillment and ease of use exert limited direct influence once satisfaction is included, whereas logistics service quality, customer service, and economic efficiency retain positive direct effects. This pattern aligns with the premise that satisfaction is the proximal antecedent of continuance and repurchase while upstream cues act mainly through satisfaction, an idea supported by Expectation Confirmation Theory and value based models of electronic commerce loyalty (Anderson & Srinivasan, 2003; Bhattacharjee, 2001). Means Ends chain theory clarifies why

certain dimensions still show direct paths: logistics quality, responsive service, and economic efficiency deliver powerful consequences such as risk reduction, fairness restoration, and concrete value realization that connect immediately to terminal values of health, safety, fairness, and frugality, yielding observable effects on repurchase beyond satisfaction (Reynolds & Gutman, 2001).

In this context, the non-significant direct path from fulfillment to repurchase intention is attributable to the structure of China's fresh-food retail landscape. In many large and medium cities, residents can reach food markets and small groceries within a short walking distance because urban planning prioritizes a "fifteen-minute community life circle," which lowers switching costs to offline channels and weakens any standalone pull from delivery fulfillment (Ma et al., 2023; Wu et al., 2021). Wet markets remain central in everyday food procurement and are valued specifically for the ability to handpick items and verify freshness through sensory inspection and trusted vendor relationships, practices that online fulfillment cannot replicate even when delivery is fast and accurate (Zhong et al., 2020; Zhong et al., 2018). Consumer research further shows that haptic information strongly shapes quality judgments, especially for food, reinforcing the preference for touch-based evaluation that privileges offline purchase occasions (Peck & Childers, 2003). Recent survey evidence from Beijing also indicates that while electronic commerce usage rose during the pandemic, physical channels such as wet markets and supermarkets continue to serve substantial shares of household food shopping, underscoring the availability of nearby alternatives to online fulfillment (Chen et al., 2023). Under these conditions, excellent fulfillment enhances satisfaction but does not independently trigger repeat purchasing; instead, repeat purchasing follows the confirmation-to-satisfaction mechanism highlighted in continuance research (Bhattacharjee, 2001).

The logistics service quality of fresh e-commerce has a positive impact on customers' willingness to repeat purchases. This finding aligns with previous research conclusions (Monoarfa et al., 2024; Wanping, 2024). This conclusion was further validated through in-depth analysis of customer reviews. The frequently mentioned terms related to logistics service quality in customer reviews, such as "Express Delivery", "Door to Door Delivery", "On Time", and "Fast", reflect customers' requirements for logistics speed and convenience. Cold Chain, Ice Pack, Freezing, and Insulated Box reflect customers' strict requirements for fresh e-commerce in maintaining product freshness. Packaging "," Plastic Bag "," Packaging Bag "," Packaging Box "also indicate customers' requirements for product packaging.

This study discovered that the ease of use of fresh e-commerce did not positively influence customers' willingness to repeat purchases. This finding contrasts with previous research indicating that e-commerce platform usability generally has a positive impact on customer behavior (Vicente Nieto & Hoorn, 2023). Classic TAM/UTAUT studies generally report that perceived ease of use or effort expectancy fosters intention at the adoption stage (Davis, 1989). However, continuance models argue that once users are onboard, satisfaction dominates while ease of use becomes a hygiene factor with little incremental effect on continued use (Bhattacharjee, 2001). Empirical evidence from adjacent contexts supports this attenuation: effort expectancy has shown null or weak effects on continuance for food-delivery and other mature app categories (Ahn, 2022; Yap & Lee, 2023; Zanetta et al., 2021). The grocery category further accentuates this pattern. Repurchase decisions hinge on fulfillment quality, including freshness, accurate picking, and on-time delivery, as well as post-delivery service, which shape satisfaction, trust, and perceived value more strongly than interface usability alone (Javed & Wu, 2020). Studies on online groceries also note that perceived online "complexity" can deter repeat buying, implying usability matters mainly

when it fails, not when it merely meets expectations (Hansen, 2006). In markets where major platforms have achieved usability parity, ease of use likely exhibits a ceiling effect; in such settings, price and delivery reliability become decisive for repurchase. Recent work reports statistically non-significant effects of perceived ease of use (and sometimes usefulness) on repurchase intention in e-commerce samples, consistent with our finding (Nuralam et al., 2024).

Customer service in fresh e-commerce positively impacts customers' willingness to repeat purchases. Customer review keywords related to customer service include "after-sales," "refund," "last time," "return," "service attitude," "merchant," "store," and "customer." Customers' attention to customer service primarily revolves around the following aspects: After-sales Service: When encountering issues during the purchasing process, customers anticipate receiving prompt and effective after-sales service. Refund and Return Policy: Customers place significant emphasis on refund and return policies, reflecting their concern about shopping risks. Service Attitude: Customers hold high expectations for the attitude and service quality of customer service personnel. High-quality after-sales service can resolve customer issues, enhance their shopping experience, and influence their decision to repurchase.

Economic efficiency in fresh e-commerce positively impacts customers' repurchase intention. The following comment theme words related to economic efficiency include: cost-effective, cheap price, good quality and low price, and price-performance ratio. Economic efficiency allows e-commerce platforms to offer goods and services at reduced prices, making them highly appealing to price-sensitive consumers. Products that offer both high quality and affordability can earn customers' trust and loyalty, encouraging repeat purchases.

Cost-effectiveness is a crucial factor for customers when selecting goods and services. This study's findings align closely with previous research on the relationship between e-commerce economic efficiency and customer behavior (Zhang & Nuangjamnong, 2022). These studies generally suggest that e-commerce platforms with high economic efficiency can provide superior quality goods and services while maintaining price advantages, thereby attracting more customers and enhancing customer satisfaction and loyalty.

5.2.3 Research Objective 3: To explore the impact of consumer satisfaction on consumer repurchase intention

Customer satisfaction itself exerts a strong positive effect on repurchase intention. This is coherent with the Expectation Confirmation sequence from expectations to perceived performance to confirmation to satisfaction to continuance, and with the Stimulus Organism Response account that internal states generate approach behavior (Mehrabian & Russell, 1974; Oliver, 1980).

Fresh e-commerce customer satisfaction has a positive effect on customer repurchase intention. Next, this study examines the positive impact of customer satisfaction on customer repurchase intention in the context of fresh e-commerce and further analyzes it in conjunction with the comment theme words related to customer satisfaction.

Satisfied, Good Review, Great, Very Good: These words indicate that the customer is satisfied with the purchasing experience or service, and has given positive reviews regarding product quality, price, delivery speed, and other aspects. An increase in satisfaction will enhance customers' trust and loyalty towards the platform, thereby increasing the likelihood of repeat purchases.

Bad Review, Disappointing, Too Bad, Waste: These negative reviews reflect customers' dissatisfaction and disappointment, which may be caused by poor product quality, delayed delivery, poor service attitude, and other reasons. Negative reviews can lower customer satisfaction, subsequently affecting customers' willingness to make repeat purchases.

Happy, Family, Worry, Like: "Happy" and "Like" indicate that customers are pleased and enjoy the shopping experience, which is usually related to the product meeting their needs, exceeding their expectations, or providing a good shopping experience. "Family" may imply that shopping is for the family, emphasizing the practicality or suitability of the goods for household use. "Worry" may reflect customers' concerns or doubts before making a purchase, but if the final shopping experience is positive, these concerns may turn into satisfaction.

In the context of customer satisfaction, the rating system is typically employed to quantify customer sentiment, where a high score indicates high satisfaction and a low score indicates the opposite. Ratings can serve as an important indicator for predicting customers' willingness to repurchase.

Customer satisfaction has a significant positive impact on customers' willingness to repurchase. Fresh e-commerce platforms should pay attention to customer feedback, improve product quality and service levels, and prioritize customer satisfaction as the core driving force to promote customer repurchasing and word-of-mouth dissemination, thereby achieving sustainable development.

5.2.4 Research Objective 4: To assess the mediating impact of consumer satisfaction on service quality and consumer repurchase intention

The mediating role of satisfaction between service quality and repurchase intention is consistent with three theoretical lenses. In the Means–Ends view, service attributes generate functional and affective consequences that realize terminal values such as assurance and value for money; satisfaction is the integrated evaluation of that realization and therefore increases the likelihood of repurchase (Reynolds & Gutman, 2001). In the S–O–R framework, service quality functions as a stimulus that shapes the organism state of satisfaction, which in turn elicits the response of repurchase intention (Eroglu et al., 2001). In expectation–confirmation theory, perceived performance relative to prior expectations produces confirmation or disconfirmation, which forms satisfaction and subsequently predicts repurchase intention (Oliver, 1980). Taken together, these perspectives converge on the same prediction: higher service quality raises satisfaction, and satisfaction transmits this effect to repurchase intention.

Customer satisfaction in fresh e-commerce serves as a mediator between service quality and customer repurchase intention. The mediating role of customer satisfaction is reflected in multiple aspects, including the impact of fulfillment, Logistics Service Quality, ease of use, customer service, and economic efficiency on repurchase intention.

When fresh e-commerce can accurately and timely fulfill orders, including the freshness, accuracy, and completeness of the goods, customers will feel satisfied. This satisfaction will translate into trust and reliance on the platform, thereby increasing the willingness to make another purchase. Therefore, customer satisfaction plays a mediating role between fulfillment and willingness to repurchase (Demirbaş et al., 2022).

The quality of logistics services directly affects customers' shopping experience, encompassing factors such as delivery speed, delivery accuracy, and packaging integrity. When the quality of logistics services is high, customers' satisfaction with the platform will also increase. This satisfaction will encourage customers to be more willing to choose this platform for future purchases, thereby enhancing their intention to repurchase. Therefore, customer satisfaction also plays a mediating role between logistics service quality and willingness to repurchase.

The usability of the fresh e-commerce platform includes interface friendliness, ease of operation, and accessibility of information. When the platform is easy to use and provides clear shopping guidance, customers will feel satisfied. This satisfaction helps enhance customers' shopping experience and loyalty, thereby increasing their willingness to make repeat purchases. Therefore, customer satisfaction also plays a mediating role between ease of use and willingness to repurchase.

High-quality customer service encompasses timely response, professional answers, problem-solving capabilities, and more. When customers encounter problems, being able to receive timely and effective assistance and resolution will enhance their satisfaction with the platform. This satisfaction will translate into trust and goodwill towards the platform, thereby increasing the willingness to make another purchase. Therefore, customer satisfaction also plays a mediating role between customer service and willingness to repurchase.

Economic efficiency typically refers to aspects such as price reasonableness and high cost-effectiveness. When customers perceive that purchasing fresh products on the platform offers high cost-effectiveness, they will feel satisfied with the platform. This satisfaction will

encourage customers to continue choosing this platform for purchasing goods in the future, thereby enhancing their willingness to make repeat purchases. Therefore, customer satisfaction also plays a mediating role between economic efficiency and willingness to repurchase.

In summary, customer satisfaction plays an important mediating role in fresh e-commerce, connecting multiple key factors that influence the willingness to repurchase. To enhance customers' willingness to repurchase, fresh e-commerce platforms should focus on and optimize aspects such as fulfillment, logistics service quality, usability, customer service, and economic efficiency, in order to improve customer satisfaction and loyalty.

5.3 Management Insights for Fresh E-commerce Platforms

The service quality of fresh e-commerce is not only directly related to customer satisfaction, but also indirectly and profoundly affects customers' repurchase intention. In view of this, the following puts forward a series of strategic suggestions aimed at improving the service quality of fresh e-commerce, in order to win customers' favor and loyalty in the fierce market competition.

In terms of fulfillment, ensure that the product description is accurate and consistent with the actual performance. Strengthen the monitoring of product quality to avoid selling inferior, smelly (such as Bad Fruit, Strange Smell) or non-compliant goods. Accurately label the net weight, size, and other information of products to avoid returns and exchanges caused by discrepancies in weight and size. For fresh products, ensure freshness and avoid selling expired or spoiled goods.

In terms of ease of use, simplify the shopping process, design a concise and clear shopping interface, and reduce cumbersome steps in the shopping process. Provide convenient payment methods to improve payment efficiency. Enhance user experience by providing personalized product recommendations based on customers' shopping habits, thereby improving the shopping experience.

In terms of customer service, the fresh e-commerce platform can strive to improve its after-sales service system and ensure the provision of rapid response services, including timely refund and return processing. For customers with poor last shopping experience, the platform should provide additional compensation or preferential measures to improve customer satisfaction. At the same time, it is very important to improve the service attitude. The platform should respect every customer and answer their questions patiently and carefully to cultivate a good service atmosphere. In addition, it is also very important to establish effective communication channels with customers. The platform should collect and seriously consider customers' feedback and suggestions in time, so as to continuously optimize services and achieve continuous improvement.

In the realm of Logistics Service Quality, fresh e-commerce enterprises can enhance logistics efficiency by ensuring punctual and swift deliveries (On Time, Fast), thereby minimizing customers' waiting periods. For perishable goods, cold chain transportation is provided to guarantee freshness throughout the shipping process. Furthermore, packaging optimization involves the use of specialized materials (such as ice packs and thermal insulation boxes) to safeguard the integrity of products during transit. By refraining from using non-eco-friendly packaging options (like plastic bags), enterprises can further elevate their environmental image.

In terms of Economic Efficiency, fresh e-commerce platforms can offer cost-effective products by ensuring that their quality matches their price, thereby delivering high value for money. By optimizing procurement, warehousing, and logistics processes, these platforms can reduce costs and provide consumers with more affordable pricing. Additionally, they can refine their pricing strategies by flexibly adjusting them according to market demands and competitive landscapes, ensuring competitiveness. Various promotional activities, such as discounts and satisfaction-based rebates, are also offered to attract consumer purchases. The survey shows that Chinese fresh e-commerce consumers prefer direct discounts (52.1%) and discounts that meet certain conditions (46.0%) as promotion methods (Yang et al., 2024).

5.4 Contribution of the Study

Drawing upon the analytical discussions and considering its theoretical and managerial implications, it is evident that this research has made significant contributions in several key areas: broadening the scope of research, establishing a novel framework for hypothesis testing, and deriving practical management recommendations. These contributions not only effectively bridge the gap between theory and practice but also provide invaluable decision-making support for various stakeholders in their operational practices.

5.4.1 Theoretical Contribution

This study makes several significant contributions to the existing literature by conducting a comprehensive analysis of multiple dimensions of service quality within the context of China's fresh e-commerce industry. Specifically, by focusing on key dimensions such as Fulfillment, Ease of Use, Customer Service, Logistics Service Quality, and

Economic Efficiency, the research provides a nuanced and detailed understanding of how these various aspects collectively shape customer perceptions and behaviors. This holistic approach not only offers a more comprehensive view of service quality but also enriches the theoretical framework in the specialized domain of fresh e-commerce, thereby filling a gap in the current literature.

Understanding the multifaceted nature of service quality is crucial for e-commerce platforms, especially those operating in the highly competitive and rapidly evolving fresh e-commerce sector. By empirically testing the direct impact of each service quality dimension on customer satisfaction and repurchase intention, this study provides valuable empirical support for theoretical propositions. This contribution is particularly significant as it validates or refutes existing theories, thereby offering concrete evidence for the relationships between service quality attributes and key customer outcomes. Such insights are essential for developing effective strategies aimed at enhancing customer satisfaction and loyalty in the Chinese fresh e-commerce industry. This means identifying specific areas of service quality that need improvement to drive customer satisfaction and, ultimately, foster long-term loyalty.

By verifying the direct effect of customer satisfaction on repurchase intention, this study reinforces the importance of customer satisfaction as a key driver of loyalty in e-commerce settings. This finding is particularly relevant in the context of fresh e-commerce, where customer retention is critical due to the perishable nature of products and the high competition among platforms. Aligning with and extending existing theories on customer behavior, this study strengthens the theoretical foundation in the area of repurchase decisions. For businesses, understanding the pivotal role of customer satisfaction in driving loyalty

underscores the need to prioritize initiatives that enhance the overall customer experience, thereby fostering positive repurchase behaviors.

This study further examines the mediating effect of customer satisfaction, providing innovative insights into the underlying mechanisms through which service quality dimensions influence repurchase intention. Specifically, by highlighting the intermediary role of customer satisfaction, this analysis not only supports the theoretical significance of customer satisfaction as a mediator but also offers practical implications for managing customer expectations and experiences. This means that enhancing service quality dimensions such as fulfillment and customer service can have a cascading effect on customer satisfaction, which in turn drives repurchase intention. This finding underscores the importance of a holistic approach to service quality management, where businesses need to focus not only on individual service quality attributes but also on how these attributes collectively impact the overall customer experience.

5.4.2 Practical Implication

This study, which draws on large scale review analysis and structural equation modeling, finds that logistics service quality, customer service, and economic efficiency significantly increase repurchase intention, while fulfillment accuracy and platform usability mainly raise customer satisfaction and thereby influence repurchase through the mediating role of satisfaction. Building on these findings, platforms should follow a focus and institutionalize approach that concentrates action into three practical steps and then embeds those steps into daily operations.

The first step is to raise logistics service quality and make delivery on the promised time and in intact condition a non-negotiable commitment. Companies should strengthen the

entire cold chain and reduce loss through arrival temperature checks, alerts for abnormal temperatures, and clear rules on packaging integrity and responsibility for damage. Time slot promises should be supported by minute level workforce scheduling, elastic peak capacity, and forward stocking in local facilities so that reliability is visible to customers. Management should track and publish key performance indicators that are tied to incentives, including the percentage of orders delivered on time and in full, the temperature compliance rate, the rate of damage and picking errors, and the rate of compensation for late deliveries. A target of at least ninety five percent on time and in full performance is recommended so that operational reliability translates into repeat purchases.

The second step is to redesign customer service around compensate first and verify later with one-touch resolution. A tiered service system should combine intelligent routing to self-service for simple requests, clear standard operating procedures for human agents, and a fast track for perishable quality issues and delivery delays, such as a one-click refund option. Day-to-day management should focus on first contact resolution, twenty-four-hour case closure, post-sale customer satisfaction scores, and net promoter scores. For high-frequency issues, teams should run a loop of root cause identification, corrective action, and results verification so that complaints decline and trust increases.

The third step is to enhance both perceived economic efficiency and ease of use. Platforms should keep memberships, promotion rules, free shipping thresholds, and pricing structures stable, transparent, and predictable to prevent distorted price expectations. A monitoring system can include a same-city, same-item net price index and a measure of member net price consistency to safeguard value perception. On the product side, the process from search to checkout should be simplified, delivery progress should be clearly visible,

and customers should have easy reordering options like one-click reorder, frequently bought lists, and baskets linked to recipes. Substitution rules for out-of-stock items should be straightforward, and information about freshness and packaging should be fully disclosed so that convenience and certainty improve satisfaction and, through mediation, boost repurchase.

To turn these improvements into organizational capabilities, platforms should treat user reviews as data assets and establish a sustained voice of the customer loop that employs topic modeling and aspect-level sentiment analysis. Each month, the company should identify the main pain points and highlights, assign a single owner to address them, track progress, and link changes back to satisfaction and repurchase metrics to foster a cycle of hearing, fixing, and verifying. Implementation should also align with the business model. Front warehouse models benefit from wave picking, minute-level scheduling, and fixed compensation for late or incorrect orders. Integrating store and warehouse operations requires dedicated in-store picking paths and chilled buffer areas with separate flows for online and offline processes to maintain stability during peak times. Community group buying demands standardized cold storage conditions at pickup points, clear rules for overdue orders, and detailed standard operating procedures for group leaders and after-sales coordination. General marketplaces should establish service level commitments for merchant quality checks, shipping deadlines, and after-sales handling, then tier merchants based on compliance and impose penalties to eliminate consistently poor performers and enhance overall supply quality.

For public governance, regulators can build consumer trust and promote fair competition by addressing high-risk failure points such as spoilage, delays, deceptive

promotions, and slow after-sales responses. This can be achieved through clearer standards and disclosures for cold chain logistics of fresh products, last-mile delivery commitments, time limits for after-sales responses, and compensation rules. Regulators can also advocate for data-driven service quality monitoring, including review-based measurements and risk-tiered compliance checks that align oversight with actual consumer experiences of fresh e-commerce.

Consumers can leverage these insights by choosing platforms with verifiable signals of logistics reliability, responsive after-sales service, and predictable delivery prices and benefits. During checkout, they should verify cold chain labels, delivery time slot commitments, and substitution policies, while strategically using memberships and coupons to enhance value and reduce dissatisfaction triggers.

Implementation can be phased. In the first three months, platforms can launch one-click refunds for delays and quality issues, establish dashboards for logistics service quality and customer satisfaction, and refine picking, packing, and substitution procedures. From months three to six, they can implement peak period scheduling and temperature spot checks across front warehouses and store-warehouse integration models while stabilizing membership and pricing structures. Between months six and twelve, they can complete the development of a voice of the customer platform and institutionalize controlled experiments with two variants, progressing from usability to satisfaction to repurchase, while linking service level commitments and merchant tiering to settlement and traffic allocation.

Results should be monitored using a concise set of KPIs. The fulfillment metrics include the percentage of orders delivered on time and fully, average delivery time, temperature compliance rate, and rates of damage and picking errors. The service metrics

include first-contact resolution, a 24-hour closure rate, and complaint rate. The value metrics include the same-city net price index and the member repurchase rate. The satisfaction and loyalty metrics encompass customer satisfaction score, net promoter score, monthly repurchase rate, basket size, and category breadth. The organization should continuously evaluate whether the pathway from service dimensions to satisfaction to repurchase is improving. Together, this three-step approach—focusing on logistics and after-sales as primary levers, anchoring perceived value on economic efficiency, and leveraging fulfillment and usability to drive satisfaction—can transform operational enhancements into sustained repurchase and word-of-mouth growth, while also providing regulators with a practical framework for standards and disclosures that support high-quality, sustainable growth in the fresh e-commerce sector.or.

5.5 Limitations of Study

This study relies on data collected in China, so the findings reflect the cultural, linguistic, regulatory, and market conditions of the Chinese fresh e-commerce sector. Consumption habits, expectations for delivery and after sales service, and the competitive landscape differ across countries and regions, which constrains external validity. Without additional evidence, direct generalization to other cultural contexts is not appropriate.

The service quality framework centers on five dimensions, namely fulfillment accuracy, ease of use, customer service, logistics service quality, and perceived economic efficiency. Although these dimensions are central to the fresh e-commerce experience, service quality extends beyond them. Important constructs not explicitly modeled include food safety assurance, environmental sustainability of packaging and cold chain operations, fairness and transparency of platform governance, assortment breadth and stockout

management, and the influence of recommendation and pricing algorithms. These omissions produce construct undercoverage and an incomplete measurement of service quality.

Methodologically, sentiment analysis of review text introduces several sources of error. Domain specific language such as slang, idioms, sarcasm, irony, and negation leads to misclassification of polarity and aspect level sentiment. Lexicons and models trained on general domains lack nuanced coverage of fresh product concepts, including degrees of freshness, ripeness, and temperature control incidents. Language use and platform norms evolve over time, creating distribution shift that reduces model stability and accuracy. These factors bias estimated relationships between service quality, satisfaction, and repurchase intention.

The integrity of review data presents another limitation. Online corpora include fabricated, coordinated, or incentivized content, as well as suppression or selective solicitation of reviews by sellers or platforms. Standard cleaning procedures reduce but do not eliminate manipulated content, so residual artifacts inflate or attenuate observed effects. Platform specific constraints such as character limits, moderation policies, interface design, and the availability of dialect or minority language input shape who writes and how opinions are expressed, creating language barriers and style biases that affect representativeness and expression.

Using customer reviews as the primary quantitative source captures publicly expressed attitudes but lacks direct interaction and probing with users. Reviewers form a self selected subset of the customer base and tend to overrepresent very positive or very negative experiences, heavy users, or users from specific city tiers. This selection process introduces bias and limits representativeness.

The model focuses on the pathway from service quality to satisfaction and repurchase intention while omitting important confounders such as brand reputation, absolute price level, marketing exposure, consumer demographics, and competitive intensity. The cross sectional design constrains causal claims and leaves open reverse effects; for example, customers with stronger repurchase intention tend to notice and report specific aspects of service quality. Future research can address these constraints by combining review data with surveys and experiments, expanding the construct set, validating across countries and platforms, incorporating tests and filters for manipulation, and adopting longitudinal designs that more clearly separate cause and effect.

5.6 Recommendations for Future Study

Future research should focus on comparative analyses of fresh e-commerce markets across countries with different cultural backgrounds, revealing the commonalities and differences in these markets under various cultural contexts, and providing valuable references for the global development of fresh food e-commerce.

To more accurately measure the online service quality of fresh e-commerce, future research should introduce more diversified evaluation dimensions to construct a more comprehensive and accurate service quality assessment system.

Future research should comprehensively consider more factors influencing customer satisfaction and repurchase intention, such as brand reputation, to build a more complex and realistic model of factors affecting customer satisfaction and repurchase intention.

To more accurately capture customers' true needs and satisfaction levels, future research should explore more diversified data collection and analysis methods. For example,

data can be collected through various means such as questionnaires and in-depth interviews to reveal the deep-level characteristics of customer behavior and demands.

5.7 Conclusion

The study aims to delve into the intricate relationships between different facets of fresh e-commerce service quality, customer satisfaction, and repurchase intention. By examining representative platforms in China's fresh e-commerce and analyzing 56,765 customer reviews, the study offers insights into the dynamics of this emerging market.

Firstly, the research confirms that multiple dimensions of fresh e-commerce service quality, including fulfillment, logistics, ease of use, customer service, and economic efficiency, significantly impact customer satisfaction. Customers value prompt and accurate fulfillment, efficient logistics with cold chain technology, user-friendly interfaces, responsive customer service, and cost-effective pricing. These findings align with previous studies and underscore the importance of a holistic approach to service quality improvement in fresh e-commerce.

Secondly, the study reveals that not all dimensions of service quality directly influence repurchase intention. While logistics service quality and customer service positively affect repurchase intention, fulfillment and ease of use do not exhibit a significant direct impact. This suggests that customers' decisions to reorder may be more influenced by the reliability and responsiveness of the delivery process and customer support than by product-specific factors or the usability of the platform. Economic efficiency also plays a vital role in driving repeat purchases, indicating that price competitiveness remains a key consideration for consumers.

Thirdly, customer satisfaction is found to be a critical mediator between service quality and repurchase intention. This implies that enhancing satisfaction levels across various service quality dimensions can indirectly boost customers' willingness to make repeat purchases. Fresh e-commerce platforms should therefore prioritize improving satisfaction as a strategic means of fostering customer loyalty.

In terms of managerial implications, the study provides a roadmap for fresh e-commerce platforms seeking to enhance their service quality and customer retention rates. Platforms should focus on optimizing logistics processes, strengthening customer service capabilities, ensuring cost-effective pricing strategies, and continuously improving the user experience. By addressing these key areas, platforms can not only meet but also exceed customer expectations, thereby fostering long-term loyalty and growth.

The study also acknowledges its limitations, particularly the geographical scope of data collection and the potential for additional influencing variables. Future research could expand upon these findings by exploring cross-cultural comparisons, incorporating more diverse evaluation dimensions, and considering additional factors such as brand reputation in the analysis of customer behavior.

In conclusion, this study offers valuable insights into the complex relationships between fresh e-commerce service quality, customer satisfaction, and repurchase intention. The findings provide practical guidance for platforms seeking to enhance their competitive position in this rapidly evolving market segment.

REFERENCES

- Abuzayed, A., & Al-Khalifa, H. (2021). BERT for Arabic topic modeling: An experimental study on BERTopic technique. *Procedia computer science*, 189, 191-194.
- Ahn, J. (2022). *Continuance Intention of Using Online Food Delivery Applications: Customers with Food Allergies*. The University of Mississippi,
- Akıl, S., & Ugan, M. C. (2022). E-commerce logistics service quality: customer satisfaction and loyalty. *Journal of Electronic Commerce in Organizations (JECO)*, 20(1), 1-19.
- Akmal, M. N., & Thamrin, T. (2025). The Effect of E-Service Quality, E-Trust and E-Satisfaction on Repurchase Intention through Prior Online Experience as a Moderation Variable:(Empirical Study on Tokopedia E-Commerce Service Users in Padang City). *International Journal of Economics and Management Research*, 4(2), 576-589.
- Al-Mu'ani, L., Al-Momani, M., Amayreh, A., Aladwan, S., & Al-Rahmi, W. (2024). The effect of logistics and policy service quality on customer trust, satisfaction, and loyalty in quick commerce: A multigroup analysis of generation Y and generation Z. *Uncertain Supply Chain Management*, 12(3), 1417-1432.
- Aljohani, K. (2024). The role of last-mile delivery quality and satisfaction in online retail experience: An empirical analysis. *Sustainability*, 16(11), 4743.
- Alrehili, A., & Albalawi, K. (2019). *Sentiment analysis of customer reviews using ensemble method*. Paper presented at the 2019 International conference on computer and information sciences (ICCIS).
- Anderson, R. E., & Srinivasan, S. S. (2003). E - satisfaction and e - loyalty: A contingency framework. *Psychology & marketing*, 20(2), 123-138.

- Angelov, D. (2020). Top2vec: Distributed representations of topics. *arXiv preprint arXiv:2008.09470*.
- Angelovska, N. (2023). Studying Customer E-loyalty to Online Intermediary: Case of Group Buying Site. *International Journal of Electronic Commerce Studies*.
- Anshu, K., Gaur, L., & Singh, G. (2022). Impact of customer experience on attitude and repurchase intention in online grocery retailing: A moderation mechanism of value Co-creation. *Journal of Retailing and Consumer Services*, 64, 102798.
- Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the pricing power of product features by mining consumer reviews. *Management science*, 57(8), 1485-1509.
- Artstein, R., & Poesio, M. (2008). Inter-coder agreement for computational linguistics. *Computational linguistics*, 34(4), 555-596.
- Ashfaq, M., Yun, J., Waheed, A., Khan, M. S., & Farrukh, M. (2019). Customers' expectation, satisfaction, and repurchase intention of used products online: Empirical evidence from China. *Sage Open*, 9(2), 2158244019846212.
- Bai, X., Zhang, X., Li, K. X., Zhou, Y., & Yuen, K. F. (2021). Research topics and trends in the maritime transport: A structural topic model. *Transport Policy*, 102, 11-24.
- Baker, M. J., & Hashimoto, B. (2024). Expression of customer (dis) satisfaction in online restaurant reviews: The relationship between adversative connective constructions and star ratings. *International Journal of Business Communication*, 61(1), 148-180.
- Balahur, A., Steinberger, R., Kabadjov, M., Zavarella, V., Van Der Goot, E., Halkia, M., . . . Belyaeva, J. (2013). Sentiment analysis in the news. *arXiv preprint arXiv:1309.6202*.
- Banerjee, S., Dellarocas, C., & Zervas, G. (2021). Interacting user-generated content technologies: How questions and answers affect consumer reviews. *Journal of marketing research*, 58(4), 742-761.

- Benhassen, T., El Bilali, H., & Allahyari, M. S. (2020). Impact of COVID-19 on food behavior and consumption in Qatar. *Sustainability*, 12(17), 6973.
- Bhattacharjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS quarterly*, 351-370.
- Blei, D., Carin, L., & Dunson, D. (2010). Probabilistic topic models. *IEEE signal processing magazine*, 27(6), 55-65.
- Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of machine Learning research*, 3(Jan), 993-1022.
- Blut, M., Chaney, D., Lunardo, R., Mencarelli, R., & Grewal, D. (2024). Customer perceived value: a comprehensive meta-analysis. *Journal of service research*, 27(4), 501-524.
- Blut, M., Chowdhry, N., Mittal, V., & Brock, C. (2015). E-service quality: A meta-analytic review. *Journal of retailing*, 91(4), 679-700.
- Bobalca, C., Țugulea, O., Ifrim, M., & Maha, L. (2021). Analysing the predictors of the young buyers' satisfaction in the e-retailing apparel sector. *International Journal of Retail and Distribution Management*, 1597-1620.
- Bollen, K. A., & Stine, R. A. (1992). Bootstrapping goodness-of-fit measures in structural equation models. *Sociological Methods & Research*, 21(2), 205-229.
- Borgardt, E. (2018). Conventional and extended versions of Means-End Chain theory. *Zeszyty Naukowe Uniwersytetu Ekonomicznego w Krakowie*, 975(3), 191-204.
- Brady, M. (2000). Improving your measurement of customer satisfaction: A guide to creating, conducting, analyzing, and reporting customer satisfaction measurement programs. *Journal of the Academy of Marketing Science*, 315.

- Brady, M. K., & Cronin, J., J Joseph. (2001). Some new thoughts on conceptualizing perceived service quality: a hierarchical approach. *Journal of marketing*, 65(3), 34-49.
- Brauwers, G., & Frasincar, F. (2022). A survey on aspect-based sentiment classification. *ACM Computing Surveys*, 55(4), 1-37.
- Büschken, J., & Allenby, G. M. (2016). Sentence-based text analysis for customer reviews. *Marketing Science*, 35(6), 953-975.
- Byrne, B. M. (2010). *Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming (2nd Edition)*: New York: Taylor and Francis Group Publication.
- Campello, R. J., Moulavi, D., & Sander, J. (2013). *Density-based clustering based on hierarchical density estimates*. Paper presented at the Pacific-Asia conference on knowledge discovery and data mining.
- Cao, S., Zheng, H., Lv, S., & Zhou, W. (2024). *Analyzing the Impact of Agricultural Products E-commerce Websites on Consumer Perceived Risk and Purchase Intention Based on the WebQual Model and the ES-QUAL Model*. Paper presented at the Proceedings of the 5th International Conference on Computer Information and Big Data Applications.
- Chang, H.-J., Eckman, M., & Yan, R.-N. (2011). Application of the Stimulus-Organism-Response model to the retail environment: the role of hedonic motivation in impulse buying behavior. *The International Review of Retail, Distribution and Consumer Research*, 21(3), 233-249.

- Chang, J., Gerrish, S., Wang, C., Boyd-Graber, J., & Blei, D. (2009). Reading tea leaves: How humans interpret topic models. *Advances in neural information processing systems*, 22.
- Chang, W.-J., Liao, S.-H., Chung, Y.-C., & Chen, H.-P. (2020). Service quality, experiential value and repurchase intention for medical cosmetology clinic: moderating effect of Generation. *Total Quality Management Business Excellence*, 31(9-10), 1077-1097.
- Chauhan, U., & Shah, A. (2021). Topic modeling using latent Dirichlet allocation: A survey. *ACM Computing Surveys (CSUR)*, 54(7), 1-35.
- Chen, D., Wang, C., & Liu, Y. (2023). How household food shopping behaviors changed during COVID-19 lockdown period: Evidence from Beijing, China. *Journal of Retailing and Consumer Services*, 75, 103513.
- Chen, L., Rashidin, M. S., Song, F., Wang, Y., Javed, S., & Wang, J. (2021). Determinants of consumer's purchase intention on fresh e-commerce platform: Perspective of UTAUT model. *Sage Open*, 11(2).
- Chen, S., Wang, Y., Han, S., & Lim, M. K. (2023). Evaluation of fresh food logistics service quality using online customer reviews. *International Journal of Logistics Research and Applications*, 26(8), 917-933.
- Chen, Z. (2024). Research on fresh food e-commerce helping rural revitalization. *Co-Operative Economy & Science*, 5, 75-77.
- Chinese Academy of International Trade and Economic Cooperation. (2024). *Report on the development of the instant retail industry (2024)*. Retrieved from <https://www.caitec.org.cn/upfiles/file/2024/11/20241213113011188.pdf>

- Chiu, C.-M. (2005). Applying means-end chain theory to eliciting system requirements and understanding users perceptual orientations. *Information & Management*, 42(3), 455-468.
- Churchill, J., Gilbert A, & Surprenant, C. (1982). An investigation into the determinants of customer satisfaction. *Journal of marketing research*, 19(4), 491-504.
- Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and psychological measurement*, 20(1), 37-46.
- Cole, D. A., & Preacher, K. J. (2014). Manifest variable path analysis: potentially serious and misleading consequences due to uncorrected measurement error. *Psychological methods*, 19(2), 300.
- Creswell, J. W., & Clark, V. L. P. (2017). *Designing and conducting mixed methods research*: Sage publications.
- Cuong, D. T. (2023). Determinants affecting online shopping consumers' satisfaction and repurchase intention: Evidence from Vietnam. *Innovative Marketing*, 19(1), 126-139.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.
- Davoodi, L., Mezei, J., & Heikkilä, M. (2025). Aspect-based sentiment classification of user reviews to understand customer satisfaction of e-commerce platforms: L. Davoodi et al. *Electronic Commerce Research*, 1-43.
- De Toni, D., Eberle, L., Larentis, F., & Milan, G. S. (2018). Antecedents of perceived value and repurchase intention of organic food. *Journal of Food Products Marketing*, 24(4), 456-475.
- Demirbaş, E., Gültekin Salman, G., & Uray, N. (2022). From E-Satisfaction to E-Repurchase Intention: How Is E-Repurchase Intention Mediated by E-Satisfaction and

- Moderated by Traditional Shopping Attitudes? In *New Perspectives in Operations Research and Management Science: Essays in Honor of Fusun Ulengin* (pp. 261-292): Springer.
- Deniz, E., Erbay, H., & Coşar, M. (2022). Multi-label classification of e-commerce customer reviews via machine learning. *Axioms*, 11(9), 436.
- Diansubao. (2025). *2024 Annual Report on Consumer Complaints Against Internet Consumption Platforms in China*. Retrieved from <https://www.100ec.cn/zt/sxdsy/img/bg.docx>
- Dieksona, Z. A., Prakosoa, M. R. B., Qalby, M. S., Putraa, M. S. A. F. S., Achmada, S., & Sutoyoa, R. (2023). Sentiment analysis for customer review: Case study of Traveloka. *Procedia computer science*, 216, 682-690.
- Dieng, A. B., Ruiz, F. J., & Blei, D. M. (2020). Topic modeling in embedding spaces. *Transactions of the Association for Computational Linguistics*, 8, 439-453.
- Do, Q. H., Kim, T. Y., & Wang, X. (2023). Effects of logistics service quality and price fairness on customer repurchase intention: The moderating role of cross-border e-commerce experiences. *Journal of Retailing and Consumer Services*, 70, 103165.
- Du, H., & Lu, K. (2023). Visualization service investment strategies for a self-operated fresh agricultural product e-tailer. *Journal of Retailing and Consumer Services*, 75, 103455.
- Du, R. (2023). The Impact Mechanism of Customer Satisfaction on Repurchase Intention in Fresh Agricultural E-commerce Platforms: The Mediating Role of Customer Trust and the Moderating Effect of Switching Costs. *Journal of Anhui Agricultural Sciences*, 51(22).

- Durmaz, A., Dursun, İ., & Kabadayi, E. T. (2020). Mitigating the effects of social desirability bias in self-report surveys: Classical and new techniques. In *Applied social science approaches to mixed methods research* (pp. 146-185): IGI Global Scientific Publishing.
- Egger, R., & Yu, J. (2022). A topic modeling comparison between lda, nmf, top2vec, and bertopic to demystify twitter posts. *Frontiers in sociology*, 7, 886498.
- Enders, C. K. (2022). *Applied missing data analysis*: Guilford Publications.
- Eroglu, S. A., Machleit, K. A., & Davis, L. M. (2001). Atmospheric qualities of online retailing: A conceptual model and implications. *Journal of Business research*, 54(2), 177-184.
- Fanani, R. I. Z. (2020). The Impact of E-Service Quality on E-Satisfaction and Implications on B2C shopee. com the online Repurchase: A case study of Indonesia. *International Journal of Advances in Scientific Research and Engineering (IJASRE)*, 6(7), 1-9.
- Fang, Y., Qureshi, I., Sun, H., McCole, P., Ramsey, E., & Lim, K. H. (2014). Trust, satisfaction, and online repurchase intention. *MIS quarterly*, 38(2), 407-A409.
- Fassnacht, M., & Koese, I. (2006). Quality of electronic services: Conceptualizing and testing a hierarchical model. *Journal of service research*, 9(1), 19-37.
- Felix, A., & Rembulan, G. D. (2023). Analysis of Key Factors for Improved Customer Experience, Engagement, and Loyalty in the E-Commerce Industry in Indonesia. *Aptisi Transactions on Technopreneurship*, 5(2sp), 196-208.
- Ferreira, D., Barbosa, B., & Sousa, A. (2025). Perceived freshness and the intention to repurchase fresh food products online. *EuroMed Journal of Business*.

- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 18(1), 39-50.
- Foroudi, P., Tabaghdehi, S. A. H., Cillo, V., & Cuomo, M. T. (2025). E-service failure and recovery strategy in times of crisis: effect on peer attitudes, expectation and future intention. *Review of Managerial Science*, 19(2), 537-571.
- Gao, K., & Sun, J. (2019). A Research on Repurchase Behaviors of Fresh Food E-commerce Platform Users under Background of Rural Revitalization Strategies. *Journal of Jiangsu University of Science and Technology(Social Science Edition)*, 3.
- Gao, X., Shi, X., Guo, H., & Liu, Y. (2020). To buy or not buy food online: The impact of the COVID-19 epidemic on the adoption of e-commerce in China. *Plos one*, 15(8), e0237900.
- Gelman, A., & Shalizi, C. R. (2013). Philosophy and the practice of Bayesian statistics. *British Journal of Mathematical and Statistical Psychology*, 66(1), 8-38.
- Ghosh, M. (2018). Measuring electronic service quality in India using ES-QUAL. *International Journal of Quality and Reliability Management*, 430-445.
- Ginting, Y., Chandra, T., Miran, I., & Yusriadi, Y. (2023). Repurchase intention of e-commerce customers in Indonesia: An overview of the effect of e-service quality, e-word of mouth, customer trust, and customer satisfaction mediation. *International Journal of Data and Network Science*, 7(1), 329-340.
- Gounaris, S., Dimitriadis, S., & Stathakopoulos, V. (2010). An examination of the effects of service quality and satisfaction on customers' behavioral intentions in e - shopping. *Journal of services Marketing*, 24(2), 142-156.

- Greene, D., O’Callaghan, D., & Cunningham, P. (2014). *How many topics? stability analysis for topic models*. Paper presented at the Joint European conference on machine learning and knowledge discovery in databases.
- Grimmer, J., & Stewart, B. M. (2013). Text as data: The promise and pitfalls of automatic content analysis methods for political texts. *Political analysis*, 21(3), 267-297.
- Grönroos, C. (1984). A service quality model and its marketing implications. *European journal of marketing*, 18(4), 36-44.
- Grootendorst, M. (2022). BERTopic: Neural topic modeling with a class-based TF-IDF procedure. *arXiv preprint arXiv:2203.05794*.
- Guan, G., Liu, D., & Zhai, J. (2022). Factors influencing consumer satisfaction of fresh produce E-commerce in the background of COVID-19—a hybrid approach based on LDA-SEM-XGBoost. *Sustainability*, 14(24), 16392.
- Gummerus, J., Liljander, V., Pura, M., & Van Riel, A. (2004). Customer loyalty to content - based Web sites: the case of an online health - care service. *Journal of services Marketing*, 18(3), 175-186.
- Guo, J., Zhang, W., & Xia, T. (2023). Impact of shopping website design on customer satisfaction and loyalty: The mediating role of usability and the moderating role of trust. *Sustainability*, 15(8), 6347.
- Hansen, T. (2006). Determinants of consumers' repeat online buying of groceries. *International Review of Retail, Distribution and Consumer Research*, 16(1), 93-114.
- Harter, A., Stich, L., & Spann, M. (2025). The Effect of Delivery Time on Repurchase Behavior in Quick Commerce. *Journal of service research*, 28(2), 211-227. doi:10.1177/10946705241236961

- Heise, A. H. H., Hongladarom, S., Jobin, A., Kinder-Kurlanda, K., Sun, S., Lim, E. L., . . . Wilhelm, C. (2019). Internet research: Ethical guidelines 3.0. *WildApricot*.
- Hellier, P. K., Geursen, G. M., Carr, R. A., & Rickard, J. A. (2003). Customer repurchase intention: A general structural equation model. *European journal of marketing*, 37(11/12), 1762-1800.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, 43(1), 115-135.
- Hong, W., Zheng, C., Wu, L., & Pu, X. (2019). Analyzing the Relationship between Consumer Satisfaction and Fresh E-Commerce Logistics Service Using Text Mining Techniques. *Sustainability*, 11(13), 3570.
- Hossain, M. A., & Quaddus, M. (2012). Expectation–confirmation theory in information system research: A review and analysis. *Information Systems Theory: Explaining and Predicting Our Digital Society, Vol. 1*, 441-469.
- Hou, Z., & Wang, C. (2022). An Empirical Study on the Impact of Service Quality in Fresh Agricultural E-commerce on Customer Behavior. *Shanxi Agricultural Economy*(24), 135-137. doi:10.16675/j.cnki.cn14-1065/f.2022.24.040
- Howard, J. A., & Sheth, J. N. (1969). The theory of buyer behavior. *New York*, 145.
- Hoyle, A., Goel, P., Hian-Cheong, A., Peskov, D., Boyd-Graber, J., & Resnik, P. (2021). Is automated topic model evaluation broken? the incoherence of coherence. *Advances in neural information processing systems*, 34, 2018-2033.
- Hsiao, C., & Tang, K. (2021). Who captures whom–Pokémon or tourists? A perspective of the Stimulus-Organism-Response model. *International Journal of Information Management*.

- Hu, L.-t., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological methods*, 3(4), 424.
- Huang, J. (2022, December 16). Shenzhen received 1,704 fresh e-commerce complaints from Jan 1 to Nov 10, up 77.32% year-on-year. *China Consumers' News*. Retrieved from <https://www.ccn.com.cn/Content/2022/12-16/1722503160.html>
- Hubert, L., & Arabie, P. (1985). Comparing partitions. *Journal of classification*, 2(1), 193-218.
- Hui, G., Al Mamun, A., Reza, M. N. H., & Hussain, W. M. H. W. (2025). An empirical study on logistic service quality, customer satisfaction, and cross-border repurchase intention. *Heliyon*, 11(1).
- Iffan, M., Syafei, M. Y., & Cuong, N. D. (2024). The Mediating Roles of Customer Trust and Satisfaction in E-Service Quality and the Repurchase Intention Relationship. *Australasian Accounting, Business and Finance Journal*, 18(5).
- Ighomereho, S. O., Ojo, A. A., Omoyele, S. O., & Olabode, S. O. (2022). From service quality to e-service quality: Measurement, dimensions and model. *Journal of Management Information and Decision Sciences*, 25(1), 1-15.
- Imbayani, I. G. A., Anggraini, N. P. N., & Novarini, N. N. A. (2025). Increasing Repurchase Intention: The Mediating Role of Utilitarian Value and Experience in Perceived Ease of Use. *International Journal of Social Science and Business*, 9(1), 01-15.
- Istanbulluoglu, D., & Sakman, E. (2024). Successful complaint handling on social media predicts increased repurchase intention: The roles of trust in company and propensity to trust. *European Management Journal*, 42(1), 11-22.
- Jain, N. K., Gajjar, H., & Shah, B. J. (2021). Electronic logistics service quality and repurchase intention in e-tailing: Catalytic role of shopping satisfaction, payment

- options, gender and returning experience. *Journal of Retailing and Consumer Services*, 59, 102360.
- Javed, M. K., & Wu, M. (2020). Effects of online retailer after delivery services on repurchase intention: An empirical analysis of customers' past experience and future confidence with the retailer. *Journal of Retailing and Consumer Services*, 54, 101942.
- Jiang, L., Jun, M., & Yang, Z. (2016). Customer-perceived value and loyalty: how do key service quality dimensions matter in the context of B2C e-commerce? *Service Business*, 10, 301-317.
- Jiang, Y., Lai, P., Chang, C.-H., Yuen, K. F., Li, S., & Wang, X. (2021). Sustainable management for fresh food e-commerce logistics services. *Sustainability*, 13(6), 3456.
- Jing, L. (2021). *China's Community Group Buying Market Report*. Retrieved from <https://www.fbicgroup.com/internal-site/wp-content/uploads/documents/Chinas-Community-Group-Buying-Market-Report.pdf>
- Jiu, M., Chen, g., & Wang, Z. (2020). Development of E-commerce of Fresh Agricultural Products in China: Progress, Difficulties and Strategies. *On Economic Problems*, 12, 68-74.
- Kahn, B. E. (2018). *The Shopping Revolution: How Successful Retailers Win Customers in an Era of Endless Disruption*: Wharton Digital Press.
- Kalia, P., & Paul, J. (2021). E-service quality and e-retailers: Attribute-based multi-dimensional scaling. *Computers in Human Behavior*, 115, 106608.
- Kamboj, S., Sarmah, B., Gupta, S., & Dwivedi, Y. (2018). Examining branding co-creation in brand communities on social media: applying the paradigm of Stimulus-Organism-Response. *International Journal of Information Management*, 169-185.

- Kang, J.-W., & Namkung, Y. (2024). The role of service quality attributes and perceived value in US consumers' impulsive buying intentions for fresh food e-commerce. *Journal of Theoretical and Applied Electronic Commerce Research*, 19(3), 1893-1906.
- Kaplan, S. E., & Nieschwietz, R. J. (2003). A Web assurance services model of trust for B2C e-commerce. *International Journal of Accounting Information Systems*, 4(2), 95-114.
- Karani, A., Thanki, H., & Achuthan, S. (2021). Impact of university website usability on satisfaction: A structural equation modelling approach. *Management and Labour Studies*, 46(2), 119-138.
- Khodeir, N., & Elghannam, F. (2025). Efficient topic identification for urgent MOOC Forum posts using BERTopic and traditional topic modeling techniques. *Education and Information Technologies*, 30(5), 5501-5527.
- Kim, C., Galliers, R. D., Shin, N., Ryoo, J.-H., Kim, J., & applications. (2012). Factors influencing Internet shopping value and customer repurchase intention. *Electronic Commerce Research*, 11(4), 374-387.
- Kim, Y.-J., & Kim, H.-S. (2022). The impact of hotel customer experience on customer satisfaction through online reviews. *Sustainability*, 14(2), 848.
- Kline, R. B. (2023a). *Principles and practice of structural equation modeling*: Guilford publications.
- Kline, R. B. (2023b). *Principles and practice of structural equation modeling*: Guilford publications.
- Kong, D. (2021). Market regulators received 2.13 million consumer complaints in 2020. *People's Daily Overseas Edition*, p. 03. Retrieved from https://paper.people.com.cn/rmrhwb/html/2021-03/17/content_2038548.htm

- Konuk, F. A. (2019). The influence of perceived food quality, price fairness, perceived value and satisfaction on customers' revisit and word-of-mouth intentions towards organic food restaurants. *Journal of Retailing and Consumer Services*, 50, 103-110.
- Koufaris, M. (2002). Applying the technology acceptance model and flow theory to online consumer behavior. *Information systems research*, 13(2), 205-223.
- Krishnan, A. (2023). Exploring the power of topic modeling techniques in analyzing customer reviews: A comparative analysis. *arXiv preprint arXiv:2308.11520*.
- Ladhari, R. (2008). Alternative measures of service quality: a review. *Managing service quality: An international journal*, 18(1), 65-86.
- Ladhari, R. (2010a). Developing e-service quality scales: A literature review. *Journal of retailing consumer services*, 17(6), 464-477.
- Ladhari, R. (2010b). Developing e-service quality scales: A literature review. *Journal of Retailing and Consumer Services*, 17(6), 464-477.
- Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *biometrics*, 159-174.
- Lau, J. H., Newman, D., & Baldwin, T. (2014). *Machine reading tea leaves: Automatically evaluating topic coherence and topic model quality*. Paper presented at the Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics.
- Le, T. Q., Wu, W.-Y., Liao, Y.-K., & Phung, T. T. T. (2022). The extended SOR model investigating consumer impulse buying behavior in online shopping: a meta-analysis. *Journal of Distribution Science*, 20(2), 1-9.
- Lee, D. D., & Seung, H. S. (1999). Learning the parts of objects by non-negative matrix factorization. *nature*, 401(6755), 788-791.

- Lee, G. G., & Lin, H. F. (2005). Customer perceptions of e - service quality in online shopping. *International Journal of Retail & Distribution Management*, 33(2), 161-176.
- Lee, J. E., & Chen-Yu, J. H. (2018). Effects of price discount on consumers' perceptions of savings, quality, and value for apparel products: mediating effect of price discount affect. *Fashion and Textiles*, 5(1), 1-21.
- Lee, S.-H., & Cha, S.-S. (2020). Consumers' choice for fresh food at online shopping in the time of covid19. *유통과학연구*, 18(9), 45-53.
- Lee, S.-H., KWAK, M.-K., & CHA, S.-S. (2020). Consumers' choice for fresh food at online shopping in the time of covid19. *Journal of Distribution Science*, 18(9), 45-53.
- Lee, V., Park, S., & Lee, D. (2022). The effect of e-commerce service quality factors on customer satisfaction, purchase intention, and actual purchase in Uzbekistan. *Global Business & Finance Review (GBFR)*, 27(3), 56-74.
- Lei, P. W., & Wu, Q. (2007). Introduction to structural equation modeling: Issues and practical considerations. *Educational Measurement: issues and practice*, 26(3), 33-43.
- Li, Z., Mao, A., Stephens, D., Goel, P., Walpole, E., Dima, A., . . . Boyd-Graber, J. (2024). Improving the tenor of labeling: Re-evaluating topic models for content analysis. *arXiv preprint arXiv:2401.16348*.
- Lin, J. (2020). Research on the Influence of Consumer's Purchase Intention of Fresh E-commerce in Background of New Retail. *Journal of North China University of Science and Technology(Social Science Edition)*, 20(02), 25-31+36.

- Lin, J., Li, T., & Guo, J. (2021). Factors influencing consumers' continuous purchase intention on fresh food e-commerce platforms: An organic foods-centric empirical investigation. *Electronic Commerce Research and Applications*, 50, 101103.
- Lin, X., Mamun, A. A., Yang, Q., & Masukujjaman, M. (2023). Examining the effect of logistics service quality on customer satisfaction and re-use intention. *Plos one*, 18(5), e0286382.
- Lindelöf, G., Aledavood, T., & Keller, B. (2023). Dynamics of the negative discourse toward COVID-19 vaccines: topic modeling study and an annotated data set of Twitter posts. *Journal of Medical Internet Research*, 25(1), e41319.
- Liu, C., Marchewka, J. T., Lu, J., & Yu, C.-S. (2005). Beyond concern—a privacy-trust-behavioral intention model of electronic commerce. *Information Management* 42(2), 289-304.
- Liu, H., & Hu, B. (2023). Evolution, Characteristics and Driving Mechanism of Fresh Produce E-commerce Model. *Journal of Administration and Management Institute of Ministry of Agriculture and Rural Affairs*, 14(03), 16-24.
- Liu, J., Zhou, Y., Jiang, X., Zhang, W. J. B. M. I., & Making, D. (2020). Consumers' satisfaction factors mining and sentiment analysis of B2C online pharmacy reviews. 20, 1-13.
- Liu, M., Jia, W., Yan, W., & He, J. (2023). Factors influencing consumers' repurchase behavior on fresh food e-commerce platforms: An empirical study. *Advanced Engineering Informatics*, 56, 101936.
- Loiacono, E. T., Watson, R. T., & Goodhue, D. L. (2007). WebQual: An instrument for consumer evaluation of web sites. *International journal of electronic commerce*, 11(3), 51-87.

- Ma, F., & Li, C. (2020). Research on E-commerce Consumer Satisfaction Measurement of Fresh Products——Analysis based on online reviews of JD Fresh. *Price:Theory & Practice*(05), 117-120. doi:10.19851/j.cnki.cn11-1010/f.2020.05.164
- Ma, K. X., Mather, D. W., Ott, D. L., Fang, E., Bremer, P., & Miroso, M. (2022). Fresh food online shopping repurchase intention: the role of post-purchase customer experience and corporate image. *International Journal of Retail & Distribution Management*, 50(2), 206-228.
- Ma, Q. (2024). Analysis of influencing factors of fresh e-commerce development based on ISM-MICMAC model. *Journal of Commercial Economics*(03), 102-105.
- MacCallum, R. (1986). Specification searches in covariance structure modeling. *Psychological bulletin*, 100(1), 107.
- Mardia, K. V. (1974). Applications of some measures of multivariate skewness and kurtosis in testing normality and robustness studies. *Sankhyā: The Indian Journal of Statistics, Series B*, 115-128.
- Mardia, K. V., Kent, J. T., & Taylor, C. C. (2024). *Multivariate analysis*: John Wiley & Sons.
- Maruyama, G. (1997). *Basics of structural equation modeling*: Sage.
- McInnes, L., Healy, J., & Melville, J. (2018). Umap: Uniform manifold approximation and projection for dimension reduction. *arXiv preprint arXiv:1802.03426*.
- Medvecki, D., Bašaragin, B., Ljajić, A., & Milošević, N. (2023). *Multilingual transformer and bertopic for short text topic modeling: The case of serbian*. Paper presented at the Conference on Information Technology and its Applications.
- Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*: the MIT Press.

- Meng, B., Zhang, X., Hua, W., Liu, L., & Ma, K. (2022). Development and application of phase change material in fresh e-commerce cold chain logistics: A review. *Journal of energy storage*, 55, 105373.
- Mensah, I., & Mensah, R. D. (2018). Effects of service quality and customer satisfaction on repurchase intention in restaurants on University of Cape Coast campus. *Journal of Tourism, Heritage Services Marketing*, 4(2), 27-36.
- Mentzer, J. T., Flint, D. J., & Hult, G. T. M. (2001). Logistics service quality as a segment-customized process. *Journal of marketing*, 65(4), 82-104.
- Mishra, A., Shukla, A., Rana, N. P., Currie, W. L., & Dwivedi, Y. K. (2023). Re-examining post-acceptance model of information systems continuance: A revised theoretical model using MASEM approach. *International Journal of Information Management*, 68, 102571.
- Mittal, V., & Kamakura, W. A. (2001). Satisfaction, repurchase intent, and repurchase behavior: Investigating the moderating effect of customer characteristics. *Journal of marketing research*, 38(1), 131-142.
- Monoarfa, T. A., Sumarwan, U., Suroso, A. I., & Wulandari, R. (2024). The crucial role of e-logistic service quality to integrated theories to predict continuance intention on fresh produce e-commerce. *Cogent Business & Management*, 11(1), 2379569.
- Mordor Intelligence. (2025). *China E-Commerce Market Size & Share Analysis - Growth Trends & Forecasts (2025 - 2030)*. Retrieved from <https://www.mordorintelligence.com/industry-reports/china-ecommerce-market>
- Morsi, S. (2023). Evaluation of Eservice Quality and its impact on Customer Satisfactions for Mobile Commerce Applications in Egypt. *Success Culture Press*.

- Myftaraj, E., & Trebicka, B. (2023). Analyzing the impact of loyalty card programs on customer behavior: insights from the Albanian market. *F1000Research*, 12, 1028.
- Nafisah, I., & Istanti, F. (2025). E-service quality, e-trust, and e-wom toward repurchase intention: The mediating role of e-customer satisfaction among tiktok shop users in Semarang. *International Journal of Applied Finance and Business Studies*, 13(1), 186-195.
- Nair, A. B., Jaison, D. T., & Anoop, V. (2024). " Hey..! This medicine made me sick": Sentiment Analysis of User-Generated Drug Reviews using Machine Learning Techniques. *arXiv preprint arXiv:2404.13057*.
- Najmani, K., Ajallouda, L., Benlahmar, E. H., Sael, N., & Zellou, A. (2023). *BERTopic and LDA, Which Topic Modeling Technique to Extract Relevant Topics from Videos in the Context of Massive Open Online Courses (MOOCs)?* Paper presented at the International Conference on Digital Technologies and Applications.
- Nanyonga, A., Keith, J., Ugur, T., & Graham, W. (2025). Is BERTopic Better than PLSA for Extracting Key Topics in Aviation Safety Reports? *arXiv preprint arXiv:2506.06328*.
- Network Economy Society. (2025). *2024 China Fresh E-commerce Market Data Report*. Retrieved from <https://www.100ec.cn/zt/sxdy/img/bg.pdf>
- Newcombe, R. G. (1998). Two - sided confidence intervals for the single proportion: comparison of seven methods. *Statistics in medicine*, 17(8), 857-872.
- Nguyen, D. Q., Billingsley, R., Du, L., & Johnson, M. (2015). Improving topic models with latent feature word representations. *Transactions of the Association for Computational Linguistics*, 3, 299-313.

- Nguyen, T. H., Ngo, H. Q., & Duong, T. T. (2021). Motivations influencing virtual supermarket shopping: An exploratory study using means-end chains analysis. *Cogent Business & Management*, 8(1), 1954491.
- Nguyen, T. H., Shirai, K., & Velcin, J. (2015). Sentiment analysis on social media for stock movement prediction. *Expert Systems with Applications*, 42(24), 9603-9611.
- Nisar, T., & Prabhakar, G. (2017). What factors determine e-satisfaction and consumer spending in e-commerce retailing? *Journal of retailing and consumer services*, 135-144.
- Nuralam, I. P., Yudiono, N., Fahmi, M. R. A., Yuliaji, E. S., & Hidayat, T. (2024). Perceived ease of use, perceived usefulness, and customer satisfaction as driving factors on repurchase intention: the perspective of the e-commerce market in Indonesia. *Cogent Business & Management*, 11(1), 2413376.
- Oh, H. (1999). Service quality, customer satisfaction, and customer value: A holistic perspective. *International journal of hospitality management*, 67-82.
- Oh, S., Ji, H., Kim, J., Park, E., & del Pobil, A. P. (2022). Deep learning model based on expectation-confirmation theory to predict customer satisfaction in hospitality service. *Information Technology & Tourism*, 24(1), 109-126.
- Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of marketing research*, 17(4), 460-469.
- Oliver, R. L. (2010). Customer satisfaction. *Wiley international encyclopedia of marketing*.
- Ou, C. X., Pavlou, P. A., & Davison, R. M. (2014). Swift guanxi in online marketplaces: The role of computer-mediated communication technologies. *MIS quarterly*, 38(1), 209-230.

- Owusu, P., Li, Z., Mensah, I. A., & Omari-Sasu, A. Y. (2025). Consumer response to E-commerce service failure: Leveraging repurchase intentions through strategic recovery policies. *Journal of Retailing and Consumer Services*, 82, 104137.
- Pan, J. (2024). Consumer Satisfaction Based on Online Reviews of Fresh Food E-commerce Platforms: Take YuanShengXian Store As an Example. *Journal of Social Systems and Policy Analysis*, 1(1), 19-25.
- Parasuraman, A., Zeithaml, V. A., & Berry, L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. 64(1), 12-40.
- Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1985). A conceptual model of service quality and its implications for future research. *Journal of marketing*, 49(4), 41-50.
- Parasuraman, A., Zeithaml, V. A., & Malhotra, A. (2005). ES-QUAL: A multiple-item scale for assessing electronic service quality. *Journal of service research*, 7(3), 213-233.
- Park, K., Cha, M., & Rhim, E. (2018). *Positivity bias in customer satisfaction ratings*. Paper presented at the Companion Proceedings of the The Web Conference 2018.
- Patterson, P. G. (1997). Modeling the determinants of customer satisfaction for business-to-business professional services. *Journal of the Academy of Marketing Science*, 4-17.
- Patwardhan, A. A. P., N. (2021). Analyzing role of E-SERVQUAL constructs for postpandemic recovery of Indian taxi aggregator services. *International Journal of Global Business and Competitiveness*, 89-102.
- Peck, J., & Childers, T. L. (2003). To have and to hold: The influence of haptic information on product judgments. *Journal of marketing*, 67(2), 35-48.
- Peng, Q., You, L., Feng, H., Du, W., Zheng, K., Zhu, F., & Xu, X. (2022). Jointly Modeling Aspect Information and Ratings for Review Rating Prediction. *Electronics*, 11(21), 3532.

- Petrie, A. (1967). *Individuality in pain and suffering*. Chicago: University of Chicago Press.
- Pham, T. M., Pandis, N., & White, I. R. (2024). *Missing data: Issues, concepts, methods*. Paper presented at the Seminars in Orthodontics.
- Phan, T., Luc, & Le, T.-H. (2023). The influence of perceived price and quality of delivery on online repeat purchase intention: The evidence from Vietnamese purchasers. *Cogent Business & Management*, 10(1), 2173838.
- Powers, D. M. (2020). Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation. *arXiv preprint arXiv:2010.16061*.
- Pradana, B. P. (2022). Investigating the Repurchase Intention of E-Commerce Users from Service Quality and Expectation-Confirmation Theory Perspective. *Jurnal Informasi dan Teknologi*, 127-135.
- Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior research methods*, 40(3), 879-891.
- Purnamasari, I., & Suryandari, R. T. (2023). Effect of e-service quality on e-repurchase intention in Indonesia online shopping: e-satisfaction and e-trust as mediation variables. *European Journal of Business and Management Research*, 8(1), 155-161.
- Quan, Y., & Xiao, Q. (2024). Study on Improving Satisfaction of New and Returning Customers for Fresh E-Commerce Platforms. *Modern Management*, 14(10), 2501-2506.
- Rachbini, W., Anggraeni, D., & Wulanjani, H. (2021). The influence of electronic service quality and electronic word of mouth (eWOM) toward repurchase intention (study on e-commerce in Indonesia). *Jurnal Komunikasi: Malaysian Journal of Communication*, 37(1), 42-58.

- Reimers, N., & Gurevych, I. (2019). Sentence-bert: Sentence embeddings using siamese bert-networks. *arXiv preprint arXiv:1908.10084*.
- Ren, Y., Qu, Y., Liang, J., & Zhao, F. (2025). Development and Validation of a Framework on Consumer Satisfaction in Fresh Food E-Shopping: The Integration of Theory and Data. *Journal of Theoretical and Applied Electronic Commerce Research*, 20(2), 114.
- Retnowati, E., & Mardikaningsih, R. (2021). Study on Online Shopping Interest Based on Consumer Trust and Shopping Experience. *Journal of Marketing Business Research*, 1(1), 15-24.
- Reynolds, T. J., & Gutman, J. (2001). Laddering theory, method, analysis, and interpretation. In *Understanding consumer decision making* (pp. 40-79): Psychology Press.
- Reynolds, T. J., & Olson, J. C. (2001). *Understanding consumer decision making: The means-end approach to marketing and advertising strategy*: Psychology Press.
- Rita, P., Oliveira, T., & Farisa, A. (2019). The impact of e-service quality and customer satisfaction on customer behavior in online shopping. *Heliyon*, 5(10).
- Robert, D., & John, R. (1982). Store atmosphere: an environmental psychology approach. *Journal of Retailing*, 34-57.
- Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder - Luis, J., Gadarian, S. K., . . . Rand, D. G. (2014). Structural topic models for open - ended survey responses. *American journal of political science*, 58(4), 1064-1082.
- Röder, M., Both, A., & Hinneburg, A. (2015). *Exploring the space of topic coherence measures*. Paper presented at the Proceedings of the eighth ACM international conference on Web search and data mining.

- Rogers, A., Kovaleva, O., & Rumshisky, A. (2021). A primer in BERTology: What we know about how BERT works. *Transactions of the Association for Computational Linguistics*, 8, 842-866.
- Salehan, M., & Kim, D. J. (2016). Predicting the performance of online consumer reviews: A sentiment mining approach to big data analytics. *Decision Support Systems*, 81, 30-40.
- Santos, J. (2003). E - service quality: a model of virtual service quality dimensions. *Managing service quality: An international journal*, 13(3), 233-246.
- Sarstedt, M. (2019). Revisiting hair et al.'s multivariate data analysis: 40 years later. In *The great facilitator: Reflections on the contributions of Joseph F. Hair, Jr. to marketing and business research* (pp. 113-119): Springer.
- Savalei, V., & Bentler, P. M. (2006). Structural equation modeling. *The handbook of marketing research: Uses, misuses, and future advances*, 330, 36.
- Scarpino, I., Zucco, C., Vallelunga, R., Luzzza, F., & Cannataro, M. (2022). Investigating topic modeling techniques to extract meaningful insights in Italian long COVID narration. *BioTech*, 11(3), 41.
- Shaoling, D. L. D. (2016). Research on Catering O2O Customer Satisfaction Based on Structural Equations - Taking "Ele.me" as an Example. *E-Commerce*.
- Shokouhyar, S., Shokoohyar, S., & Safari, S. (2020). Research on the influence of after-sales service quality factors on customer satisfaction. *Journal of Retailing Consumer Services*, 56, 102139.
- Sokolova, M., & Lapalme, G. (2009). A systematic analysis of performance measures for classification tasks. *Information processing & management*, 45(4), 427-437.

- Somprasertsri, G., & Lalitrojwong, P. (2010). Mining feature-opinion in online customer reviews for opinion summarization. *J. Univers. Comput. Sci.*, 16(6), 938-955.
- Song, H., Chu, J., Hu, Y., & Liu, X. (2013). *Semantic analysis and implicit target extraction of comments from E-commerce websites*. Paper presented at the 2013 fourth world congress on software engineering.
- Song, Y., Gui, L., Wang, H., & Yang, Y. (2023). Determinants of continuous usage intention in community group buying platform in China: Based on the information system success model and the expanded technology acceptance model. *Behavioral Sciences*, 13(11), 941.
- Songpan, W. (2017). *The analysis and prediction of customer review rating using opinion mining*. Paper presented at the 2017 IEEE 15th International Conference on Software Engineering Research, Management and Applications (SERA).
- Su, D. N., Nguyen-Phuoc, D. Q., Duong, T. H., Dinh, M. T. T., Luu, T. T., & Johnson, L. (2022). How does quality of mobile food delivery services influence customer loyalty? Gronroos's service quality perspective. *International Journal of Contemporary Hospitality Management*, 34(11), 4178-4205.
- Suhaily, L. S., Y. (2017). What effects repurchase intention of online shopping. *International Business Research*, 113-122.
- Sun, X. (2021). *Impact of Consumer Satisfaction on Fresh E-commerce Repeat Purchase Behavior*. Paper presented at the E3S Web of Conferences.
- Suryadi, D. (2020). *Predicting repurchase intention using textual features of online customer reviews*. Paper presented at the 2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy (ICDABI).

- Tang, T., Huang, L., & Chen, Y. (2020). *Evaluation of Chinese sentiment analysis APIs based on online reviews*. Paper presented at the 2020 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM).
- Tashakkori, A., & Teddlie, C. (2010). *Sage handbook of mixed methods in social & behavioral research*: sage.
- Tuncer, I. (2021). The relationship between IT affordance, flow experience, trust, and social commerce intention: An exploration using the SOR paradigm. *Technology in Society*, 65, 101567.
- Tyrväinen, O., & Karjaluo, H. (2022). Online grocery shopping before and during the COVID-19 pandemic: A meta-analytical review. *Telematics and Informatics*, 71, 101839.
- Udapa, A., Adarsh, K., Aravinda, A., Godihal, N. H., & Kayarvizhy, N. (2022). *An exploratory analysis of GSDMM and BERTopic on short text topic modelling*. Paper presented at the 2022 fourth international conference on cognitive computing and information processing (CCIP).
- Van Atteveldt, W., Van der Velden, M. A., & Boukes, M. (2021). The validity of sentiment analysis: Comparing manual annotation, crowd-coding, dictionary approaches, and machine learning algorithms. *Communication Methods and Measures*, 15(2), 121-140.
- Vazirani, M. (2022). Factors Influencing Customer Satisfaction and Repurchase Intention in Context of Online Grocery Shopping.
- Veludo-de-Oliveira, T. M., Ikeda, A. A., & Campomar, M. C. (2006). Discussing laddering application by the means-end chain theory. *The Qualitative Report*, 11(4), 626-642.

- Venkatakrishnan, J., Alagiriswamy, R., & Parayitam, S. (2023). Web design and trust as moderators in the relationship between e-service quality, customer satisfaction and customer loyalty. *The TQM Journal*, 35(8), 2455-2484.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.
- Vicente Nieto, J., & Hoorn, D. (2023). Designing for success: enhancing e-commerce purchase intention for online clothing reselling platforms: A mixed method multiple case study of usability factors and a practical usability framework for success. In.
- Wang , G., Zhang , X., Xu , F., & Ding , X. (2019, 3). The impact of electronic service quality on customer engagement: the mediating effect of customer perceived value. *Journal of Dalian University of Technology (Social Sciences)*, 67-76.
- Wang, L., Tang, Y.-M., Chau, K.-Y., & Zheng, X. (2024). Empirical research of cold-chain logistics service quality in fresh product e-commerce. *Journal of Theoretical and Applied Electronic Commerce Research*, 19(3), 2543-2556.
- Wang, X., & Xu, X. (2022). Research on the Development Status and Future Trend of Fresh E-commerce. *Logistics Sci-Tech*, 45(05), 81-83. doi:10.13714/j.cnki.1002-3100.2022.05.017
- Wang, X., & Zhang, Q. (2016). Internal Mechanism for E-commerce Solving Difficulty in Circulation of Fresh Agricultural Products: A Comparative Double-Case Study of Tmall and Tootoo. *China Soft Science*(2), 39-55.
- Wang, Y. (2021). An Empirical Study on the Influencing Factors of Customer Satisfaction in Fresh Food E-Commerce. *Trade Fair Economy*(03), 38-40.

- Wang, Y. (2023). Identification of factors influencing consumers' satisfaction with purchasing clean vegetables online—Based on JD.com online review information. *E-Commerce Letters*.
- Wang, Y., Yang, A., Li, Y., & Yang, Q. (2023). Effect of e-commerce popularization on farmland abandonment in rural China: Evidence from a large-scale household survey. *Land Use Policy*, 135, 106958.
- Wanping, Z. (2024). The Effect of Last-Mile Logistics Services Quality on Customer Loyalty in Fresh Food E-Commerce: Evidence from China. *East Asian Journal of Business Economics (EAJBE)*, 12(3), 1-10.
- Wattoo, M. U., Du, J., Shahzad, F., & Kousar, S. (2025). Shaping E-commerce Experiences: Unraveling the Impact of Service Quality on Youth Customer Behavior in a Developing Nation. *Sage Open*, 15(1), 21582440241311786.
- Webber, W., Moffat, A., & Zobel, J. (2010). A similarity measure for indefinite rankings. *ACM Transactions on Information Systems (TOIS)*, 28(4), 1-38.
- Wijaya, I. G. N. S., Triandini, E., Kabnani, E. T. G., & Arifin, S. (2021). E-commerce website service quality and customer loyalty using WebQual 4.0 with importance performances analysis, and structural equation model: An empirical study in shopee. *Register: Jurnal Ilmiah Teknologi Sistem Informasi*, 7(2), 107-124.
- Wilson, N., Keni, K., & Tan, P. H. P. (2019). The effect of website design quality and service quality on repurchase intention in the e-commerce industry: A cross-continental analysis. *Gadjah Mada International Journal of Business*, 21(2), 187-222.
- Wolfenbarger, M., & Gilly, M. C. (2003). eTailQ: dimensionalizing, measuring and predicting etail quality. *Journal of retailing*, 79(3), 183-198.

- Woodside, A., Frey, L., & Daly, R. (1989). Linking service quality, customer satisfaction, and behavior. *Marketing Health Services*, 5-17.
- Woodworth. (1929). *Psychology: A Study of Mental Life*.
- Wu, S., Yau, W.-C., Ong, T.-S., & Chong, S.-C. (2021). Integrated churn prediction and customer segmentation framework for telco business. *Ieee Access*, 9, 62118-62136.
- Wu, W., Widiatmo, G., & Riantama, D. (2023). What motivates customers to repurchase online under social distancing? *Frontiers in Psychology*, 14, 1155302.
- Xiang, W., & Cui, F. (2022). *Fresh E-commerce in Multi-Mode Development Phase - Resilience of Front Warehouse Segment and Diverse Strategies of Market Players*. Retrieved from https://pdf.dfcfw.com/pdf/H3_AP202207011575688309_1.pdf
- Xu, X.-Y., Tayyab, S. M. U., Chang, F.-K., & Zhao, K. (2021). Hierarchical value-attainment paths of CBEC consumers: a means-end-chain perspective. *Internet Research*, 31(2), 699-736.
- Xu, x., & Chen, j. (2020). *Research on the Influence of E-commerce service quality of fresh Agricultural products on customer satisfaction*. Paper presented at the E3S Web of Conferences.
- Yan, X., Guo, J., Lan, Y., & Cheng, X. (2013). *A biterm topic model for short texts*. Paper presented at the Proceedings of the 22nd international conference on World Wide Web, Rio de Janeiro, Brazil. <https://doi.org/10.1145/2488388.2488514>
- Yang, C.-C., Jou, Y.-T., & Cheng, L.-Y. (2011). Using integrated quality assessment for hotel service quality. *Quality & Quantity*, 45, 349-364.
- Yang, Q., Wang, Z.-S., Feng, K., & Tang, Q.-Y. (2024). Investigating the crucial role of logistics service quality in customer satisfaction for fresh e-commerce: A mutually

- validating method based on SERVQUAL and service encounter theory. *Journal of Retailing and Consumer Services*, 81, 103940.
- Yang, Y. (2025). Charting the path to consumer satisfaction: An innovative investigation into fresh e-commerce through text mining and spatiotemporal analysis.
- Yao, T. (2020). China's fresh e-commerce industry ecological and service quality improvement issues to discuss. *Journal of Commercial Economics*(16), 95-98.
- Yap, C. P., & Lee, W. O. (2023). *Factors influencing continuance intention to adopt online food delivery services among millennials during the Covid-19 pandemic*. Paper presented at the Proceedings of the 10th International conference on business, accounting, finance and economics (BAFE 2022).
- Yen, C. H., & Lu, H. P. (2008). Effects of e - service quality on loyalty intention: an empirical study in online auction. *Managing service quality: An international journal*, 18(2), 127-146.
- Yi, M., Chen, M., & Yang, J. (2024). Understanding the self-perceived customer experience and repurchase intention in live streaming shopping: evidence from China. *Humanities and Social Sciences Communications*, 11(1), 1-13.
- Yi, S., & Liu, X. (2020). Machine learning based customer sentiment analysis for recommending shoppers, shops based on customers' review. *Complex & Intelligent Systems*, 6(3), 621-634.
- Yin, J., & Wang, J. (2014). *A dirichlet multinomial mixture model-based approach for short text clustering*. Paper presented at the Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining.
- Yonghui Superstores Co., L. (2023). *Yonghui Group's 2023 Semi-Annual Report*. Retrieved from <https://www.yonghui.com.cn/upload/Inv/9491603.PDF>

- Yoo, B., & Donthu, N. (2001). Developing a scale to measure the perceived quality of an Internet shopping site (SITEQUAL). *Quarterly journal of electronic commerce*, 2(1), 31-45.
- Yuan, K.-H., & Bentler, P. M. (2006). structural equation modeling. *Handbook of statistics*, 26, 297-358.
- Zanetta, L. D. A., Hakim, M. P., Gastaldi, G. B., Seabra, L. M. A. J., Rolim, P. M., Nascimento, L. G. P., . . . da Cunha, D. T. (2021). The use of food delivery apps during the COVID-19 pandemic in Brazil: The role of solidarity, perceived risk, and regional aspects. *Food Research International*, 149, 110671.
- Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. *Journal of marketing*, 52(3), 2-22.
- Zeithaml, V. A. (2000). *A conceptual framework for understanding e-service quality: Implications for future research and managerial practice*. Retrieved from
- Zeithaml, V. A., Parasuraman, A., & Malhotra, A. (2002). Service quality delivery through web sites: a critical review of extant knowledge. *Journal of the academy of marketing science*, 30(4), 362-375.
- Zhang, C., Liu, H., Chen, Z., & Tang, H. (2021). *Tourism Forecast Based on Web Search Data and Sentiment Analysis of Social Network*. Paper presented at the The 2nd International Conference on Computing and Data Science.
- Zhang, H., Deng, H., Sun, Q., & Zhu, L. (2025). Customer satisfaction in online-to-offline commerce: a fresh product perspective. *British Food Journal*, 127(13), 284-300.
- Zhang, J. (2023). Research on the Current Situation and Operational Models of China's Fresh E-commerce. *Journal of Modern Business Research*, 25(4), 34–41.

- Zhang, W., Li, X., Deng, Y., Bing, L., & Lam, W. (2022). A survey on aspect-based sentiment analysis: Tasks, methods, and challenges. *IEEE Transactions on Knowledge and Data Engineering*, 35(11), 11019-11038.
- Zhang, Z., & Nuangjamnong, C. (2022). The impact factors toward online repurchase intention: A case study of Taobao e-commerce platform in China. *International Research E-Journal on Business and Economics*, 7(2), 35-56.
- Zhao, S., Chen, L., Liu, Y., Yu, M., & Han, H. (2022). Deriving anti-epidemic policy from public sentiment: A framework based on text analysis with microblog data. *Plos one*, 17(8), e0270953.
- Zhao, X., Lynch Jr, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of consumer research*, 37(2), 197-206.
- Zhao, Y., Xu, X., & Wang, M. (2019). Predicting overall customer satisfaction: Big data evidence from hotel online textual reviews. *International Journal of Hospitality Management*, 76, 111-121.
- Zhong, S., Crang, M., & Zeng, G. (2020). Constructing freshness: the vitality of wet markets in urban China. *Agriculture and Human Values*, 37(1), 175-185.
- Zhong, T., Si, Z., Crush, J., Xu, Z., Huang, X., Scott, S., . . . Zhang, X. (2018). The impact of proximity to wet markets and supermarkets on household dietary diversity in Nanjing City, China. *Sustainability*, 10(5), 1465.
- Zhou, Y., Aryal, S., & Bouadjenek, M. R. (2024). A Comprehensive Review of Handling Missing Data: Exploring Special Missing Mechanisms. *arXiv preprint arXiv:2404.04905*.

- Zhu, H., & Wang, C. (2024). The Impact of Service Quality of Fresh Agricultural E-commerce Platforms on Customer Loyalty. *Journal of Smart Agriculture*, 4(01), 27-30+34. doi:10.20028/j.zhnydk.2024.01.007
- Zhu, L., Xu, M., Bao, Y., Xu, Y., & Kong, X. (2022). Deep learning for aspect-based sentiment analysis: a review. *PeerJ Computer Science*, 8, e1044.