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Mining Service Quality Dimensions from User-Generated Content: A Case Study on Chinese Fresh Food E-Commerce

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Abstract

This study explores the key dimensions of service quality in China’s fresh food e-commerce sector by analyzing large-scale user-generated content (UGC) from four major platforms. Employing the BERTopic model, the research extracted 18 latent topics from 56,765 customer reviews, which were further mapped into six overarching service quality dimensions: Product Quality, Logistics & Cold Chain, Economic Efficiency, Customer Service, Platform Experience, and Packaging & Hygiene. These dimensions reflect both classical service constructs from SERVQUAL and E-S-QUAL frameworks and unique operational characteristics specific to fresh e-commerce, such as perishability and cold-chain logistics. The study demonstrates the effectiveness of topic modeling in capturing authentic consumer perceptions and offers a more context-sensitive framework for service evaluation. The findings provide theoretical contributions by refining existing models and offer actionable insights for platform operators to optimize service design, enhance customer satisfaction, and improve competitive advantage in China’s evolving digital marketplace.

Keywords: fresh food e-commerce, service quality, user-generated content, topic modeling

1. Introduction

Fresh food e-commerce refers to the online retailing of highly perishable agricultural and food products, such as fruits, vegetables, meat, egg, and seafood, via digital platforms (Sun, 2021). Unlike general merchandise e-commerce, it is characterized by short product lifecycles, high perishability, and strict demands for cold-chain logistics and timely delivery. These platforms often follow a streamlined process of order placement, intelligent sorting, cold storage, and same-day delivery to fulfill high-frequency and time-sensitive demand.

1.1 Background and Motivation

Fresh food e-commerce has been described as the "last blue ocean" of the e-commerce sector (Pan, 2024). In 2024, its transaction volume reached RMB 560.14 billion, accounting for 25.8% of urban residents' food expenditure (GonynResearch, 2025). With growing consumer reliance on online fresh purchases, market penetration is expected to rise further.

As of April 2024, over 27,000 enterprises operated in China's fresh food e-commerce sector, nearly triple the number in 2020 (GonynResearch, 2025). The market has evolved from scale expansion to quality-based competition, with platforms emphasizing service improvement to retain users and enhance brand value.

As noted by Chen et al. (2021), consumers of fresh food e-commerce platforms place great emphasis on factors such as freshness, delivery speed, product safety, and the reliability of after-sales service. In 2024, China's fresh food e-commerce sector faced widespread consumer complaints, primarily concerning product quality, delivery delays, refund issues, and poor after-sales service. Platforms like Dingdong Maicai were downgraded due to recurring service failures, reflecting persistent deficiencies in overall service quality (NetEconomy, 2025).

Given the perishable nature of fresh goods, any breakdown in packaging, logistics, or support can significantly impact the customer experience. Studies have consistently shown that service quality has a significant impact on user retention in this domain (Huang & Nuangjamnong, 2023; Kim & Yum, 2024; Wang et al., 2021). Enhancing service quality has become a strategic imperative for platforms aiming to overcome stagnation and foster sustainable growth.

1.2 Research Problem and Objective

Although China's fresh food e-commerce market has experienced robust growth in recent years, academic research on its service quality dimensions remains insufficient and highly fragmented. Existing studies have proposed various dimensions based on different perspectives, including customer perception, platform operation, and logistics efficiency. Commonly identified dimensions include delivery quality, product freshness, information quality, price/value, ease of use, and responsiveness (Chen et al., 2023; Jiang et al., 2021; Kang & Namkung, 2022, 2024). Although these studies reveal diverse consumer expectations, they often lack theoretical integration, which hinders the development of a standardized model suited to the unique features of fresh food e-commerce.

Although SERVQUAL (Parasuraman et al., 1988) and E-S-QUAL (Parasuraman et al., 2005) are widely used in e-commerce, their standardized structure limits their applicability to the current e-commerce landscape. These models overlook key features such as cold-chain reliance, time sensitivity, and quality variability. As a result, direct application may lead to measurement bias and fail to capture critical customer concerns.

At present, few studies have attempted to extract service quality dimensions from large-scale user-generated content (UGC), particularly in the context of Chinese-language platforms. Customer reviews, as first-hand data closely reflecting real user experiences, remain an underutilized resource in academic research (Malik, 2020). Most studies rely on structured surveys or expert input, resulting in models shaped by researcher assumptions rather than genuine customer perspectives. This limits validity and relevance. Given the richness of online reviews, leveraging user-generated content offers a promising data-driven approach to identifying service quality dimensions more accurately aligned with consumer perceptions. Recent work by Chen et al. (2023) has begun to explore this direction, but systematic and large-scale applications remain rare.

In response to the identified research gaps, this study aims to explore service quality dimensions in China's fresh food e-commerce through a data-driven approach. Rather than relying on predefined theoretical frameworks or closed-ended surveys, the study utilizes large-scale user-generated content (UGC) as its primary data source, enabling more authentic and granular insights into customer perceptions.

1.3 Research Significance

This study contributes to the literature on service quality in fresh food e-commerce, a field that remains underexplored despite its rapid growth. By leveraging large-scale user-generated content, it moves beyond the limitations of traditional survey-based methods and offers a consumer-centered perspective grounded in real experience. It bridges the gap between established models, such as SERVQUAL/E-S-QUAL, and the operational features of emerging e-commerce, including perishability and reliance on cold chains. The use of topic modeling represents a methodological advancement, enabling the extraction of service dimensions directly from customer narratives.

From a managerial standpoint, the findings offer practical guidance for platform operators. By identifying service aspects frequently mentioned by users, firms can prioritize improvements, optimize resource allocation, and develop customer-driven strategies. The results also support the design of evaluation systems aligned with actual consumer concerns. In a competitive and experience-oriented market, this study helps translate customer feedback into actionable service design, contributing to platform optimization and service innovation.

2. Literature Review

This section reviews two key areas: traditional service quality models, such as SERVQUAL and E-S-QUAL, and emerging data-driven approaches that use user-generated content (UGC) and text mining to identify service dimensions. This dual perspective informs the theoretical and methodological basis of the present study.

2.1 Service Quality Models

The service quality model is based on the expectation-confirmation paradigm, which views service quality as the gap between customer expectations and perceived performance (Oliver, 1980). Initially developed during a research project from 1983 to 1988, the model identifies key components of service quality and introduces the SERVQUAL scale (Parasuraman et al., 1985). The original ten dimensions—such as tangibles, reliability, and communication—were later refined due to overlap among constructs. Through empirical validation, they were reduced to five core dimensions: tangibles, reliability, responsiveness, assurance, and empathy (Parasuraman et al., 1988). These five dimensions form the basis of the SERVQUAL framework and remain widely used in service quality evaluation, as presented in Table 1.

Table 1. SERVQUAL Items

Dimension	Definition
Reliability	Consistent and precise delivery of the committed service.
Assurance	Employees' expertise and politeness instill a sense of trust and reliability.
Tangibles	The visual presentation of facilities, tools, staff, and communication aids.
Empathy	Offering personalized and attentive care to each customer.
Responsiveness	Readiness to assist customers with swift and efficient service.

Source: SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality (Parasuraman et al., 1988)

Despite SERVQUAL's influence, empirical research has revealed instability and context-dependency in its factor structure when applied across sectors such as retail and e-commerce. In response to the rise of online commerce, Parasuraman et al. (2005) proposed the E-S-QUAL model with four dimensions: efficiency, fulfillment, system availability, and privacy, which empirical studies have linked to consumer purchase intention and trust. Meta-analytic reviews by Blut et al. (2015) and Santos (2003) further identified core e-service dimensions: website design, fulfillment, customer service, security/privacy, that consistently predict perceived quality. Building on this, Ighomereho et al. (2022) proposed a seven-dimensional e-service quality model (including reliability, ease of use, security, fulfillment, responsiveness, and personalization), among which reliability, security, and fulfillment were most predictive.

However, traditional frameworks like SERVQUAL and E-S-QUAL, which were designed for standardized services and controlled interactions, lack the specificity required to address the operational complexity of fresh food e-commerce. This complexity includes high product perishability, stringent cold-chain logistics, time-sensitive delivery, fluctuating product quality, and diverse customer expectations. Empirical investigations in the context of fresh e-commerce, such as those conducted by Lee et al. (2020), Ma and Li (2020), and Hou and Wang (2022), demonstrate that dimensions such as economic efficiency, packaging and logistics quality, platform usability, and product quality significantly influence customer satisfaction and repurchase intention. Table 2 presents the views of various studies on the dimensions of e-service quality.

Table 2. Dimensions of 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 & Lin, 2005)	Website Design, Reliability, Responsiveness, Trust	4	305 Questionnaires from Online Consumers
(Yen & Lu, 2008)	Efficiency, Privacy Protection, Contact, Fulfillment, Responsiveness	5	Questionnaires of 619 bidders in the online auction (Yahoo! KiMo)
(Ladhari, 2010)	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

Table 2. continued

Author	Dimensions	Number of Dimensions	Method
(Kalia & Paul, 2021)	Efficiency, Fulfillment, System Availability, Privacy, Responsiveness, Compensation, Contact	7	Survey of 300 Consumers on Five Leading E-retailers in the Indian market
(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 & 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 & 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 & Wang, 2024)	Visibility, Reliability, Responsiveness, Convenience, Ease of Use	5	335 Questionnaires from Chinese Customers

2.2 User-Generated Content (UGC) Text Mining

User-Generated Content (UGC), particularly in the form of post-purchase customer reviews, has become an increasingly important source of data for understanding consumer perceptions and service experiences in e-commerce. These reviews reflect authentic user feedback, often containing rich emotional, behavioral, and experiential information that structured surveys may fail to capture (Dahiya et al., 2021). Unlike closed-ended questionnaire data, UGC provides spontaneous, fine-grained insights into specific service encounters, making it highly valuable for identifying service quality dimensions.

With the proliferation of user-generated content (UGC) on digital platforms, text mining has become an increasingly valuable approach for identifying service quality dimensions directly from consumer narratives. Text mining enables researchers to extract data-driven insights from large-scale, unstructured texts, providing a bottom-up perspective for developing service quality frameworks. Lu et al. (2023) developed a weighted service quality (WSQ) metric derived from customer opinions in e-commerce reviews, uncovering service dimensions that were not predefined in traditional models. In the healthcare context, Zhang et al. (2025) built a five-dimensional service quality model by applying topic modeling to online patient reviews, confirming that context-specific service attributes, such as empathy, service delivery process, and physician expertise, emerged organically from consumer expressions rather than researcher assumptions.

3. Research Methodology

This study adopts a three-stage methodology: data collection from diverse fresh food e-commerce platforms, systematic data cleaning to ensure quality, and topic modeling to extract service-related themes from large-scale customer reviews.

3.1 Data Collection

To ensure representativeness across business models in China's fresh e-commerce landscape, this study selected four leading platforms as data sources: JD Fresh (traditional e-commerce model), Dingdong Maicai (front warehouse model), Yonghui Superstores (store-warehouse integration model), and Taocaicai (community group purchase model). These platforms were selected for their broad market coverage and distinct operational models, catering to various consumer segments, including urban and rural markets (Wang & Xu, 2022).

Review data were collected for four major fresh product categories: fruits, vegetables, meat & eggs, and aquatic products, focusing on best-selling items to reflect mainstream consumption patterns and ensure sufficient review volume. Both positive and negative feedback were included to capture the full spectrum of user experience. To minimize potential sampling bias arising from the overrepresentation of extreme opinions, the dataset was balanced by including a broad range of user reviews across different products and time periods.

In total, 77,183 customer reviews were obtained between August 1, 2023, and August 1, 2024, ensuring seasonal coverage.

This study is based exclusively on publicly available consumer reviews obtained from online platforms. No personally identifiable information was collected, stored, or analyzed. The data were used solely for academic purposes, and all analyses were conducted at an aggregate level to preserve anonymity. According to institutional guidelines, studies using publicly accessible secondary data without personal identifiers are typically exempt from formal ethical clearance. Nevertheless, the research adhered to general ethical principles by ensuring that user content was treated responsibly and confidentially.

3.2 Data Preprocessing

To ensure analytical validity, a systematic data cleaning process was applied to remove noise and retain only relevant consumer reviews.

Table 3. Statistics of Collected Customer Reviews

Product Category	Data Source	Raw Review Data	Cleaned Comment Data
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

First, duplicate entries were identified and removed to prevent overrepresentation of certain opinions. Second, non-informative content such as default replies, pure symbols, numbers, or emoticons was excluded. Third, overly short comments that failed to meet a minimum length threshold were discarded, as they lacked semantic richness and could impair feature extraction. After applying these criteria, the dataset was refined from 77,183 to 56,765 valid reviews, providing a reliable foundation for subsequent analysis. The distribution of valid comments across products is shown in Table 3.

3.3 Topic Modeling using BERTopic

In service quality research based on text mining, topic modeling plays a central role in uncovering latent semantic structures within large-scale unstructured textual data. Over the past two decades, several topic modeling techniques have been developed, each with unique strengths and theoretical foundations. Table 4 summarizes the most commonly used topic modeling approaches, along with their core features and sources.

When analyzing short and informal customer reviews, it is crucial to select a topic modeling method that can accurately capture semantic nuances and generate coherent themes. Traditional methods, such as LDA, require the number of topics to be predefined and often struggle with short texts, 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. Recent research by 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. Krishnan (2023) compared LDA, NMF, PAM, Top2Vec, and BERTopic using customer review datasets. They found that BERTopic consistently produced the most meaningful and coherent topics as measured by topic coherence scores. Egger and Yu (2022) evaluated the performance of LDA, NMF, Top2Vec, and BERTopic on social media texts, demonstrating that BERTopic outperformed the others in terms of 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 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 × 384.

Table 4. Common Topic Modeling Methods in Text Mining

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 & 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 & 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)

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 both local and global relationships between clauses, thereby facilitating improved clustering performance.

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

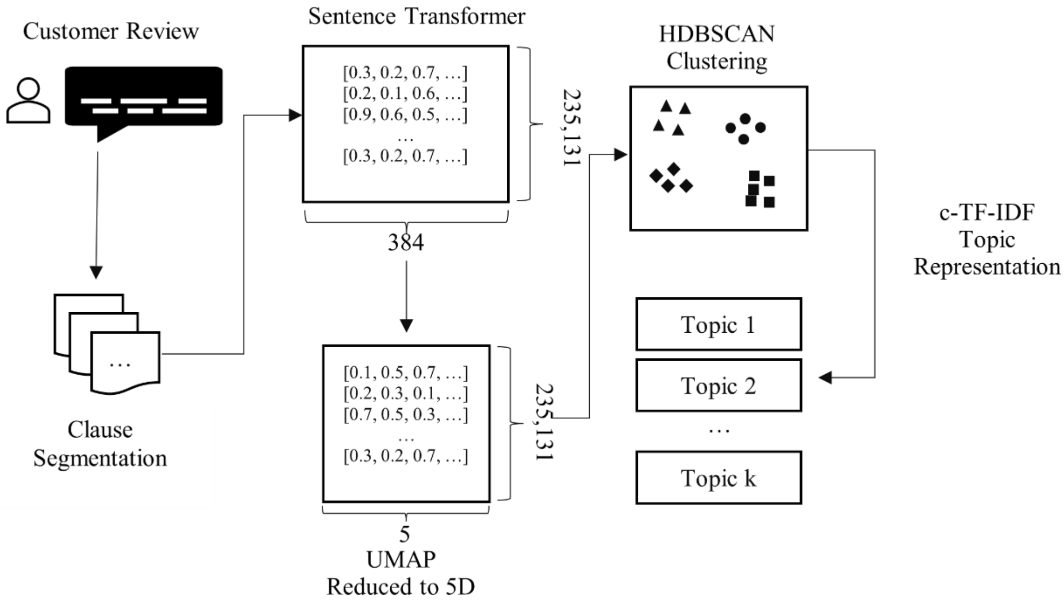

Figure 1. Topic Modeling Framework

4. Findings and Analysis

To uncover service-related themes from user reviews, BERTopic was applied to the preprocessed clause-level data. This approach identified coherent topics grounded in actual consumer feedback. The following section presents the topic modeling results, highlighting the dominant themes and keywords that reflect key aspects of service quality in fresh e-commerce.

4.1 Extracted Topics

Figure 2 displays the topic modeling output generated using BERTopic. A total of 18 topics (labeled 0–17) were identified based on the clustering of semantically similar clauses. Each topic includes a set of keywords with associated relevance scores, visualized as horizontal bars whose lengths indicate the relative importance of each term. Distinct colors are used for differentiation. The visualization aids in examining the internal structure of each topic and identifying frequently co-occurring terms.

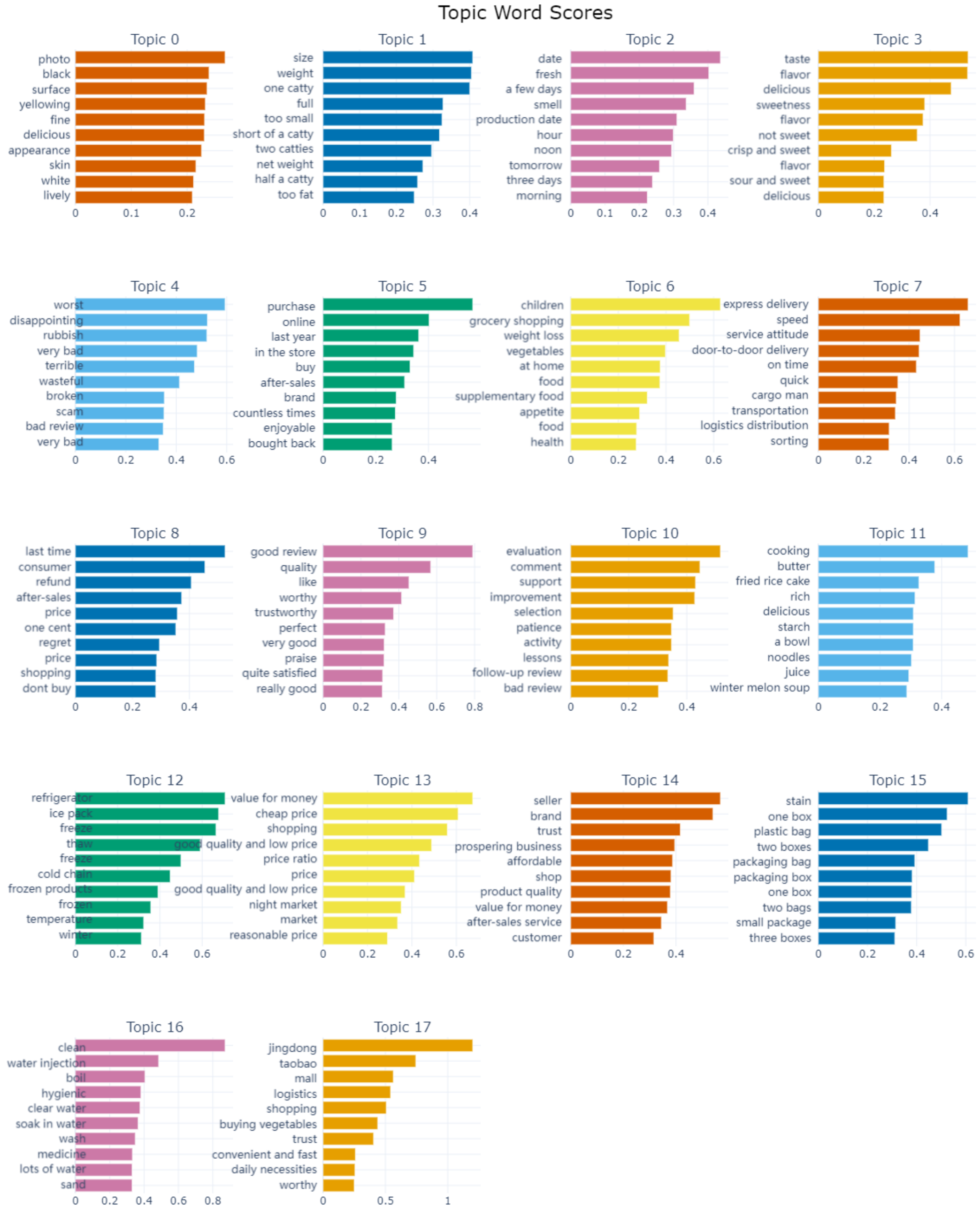

Figure 2. Topic Word Scores from Bertopic

Table 5 summarizes the detailed topic modeling results. Each topic is assigned a numerical identifier and a descriptive label. The "Count" column indicates the number of clauses associated with each topic, while "Representation" lists the top keywords that characterize the semantic content of the topic.

Table 5. Topic Modeling Outputs

Topic	Count	Name	Representation
0	21,950	0_photo_black_surface_yellowed	['photo', 'black', 'surface', 'yellowing', 'fine', 'delicious', 'appearance', 'skin', 'white', 'lively']
1	20,048	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	14,651	2_date_fresh_days_smell	['date', 'fresh', 'a few days', 'smell', 'production date', 'hour', 'noon', 'tomorrow', 'three days', 'morning']
3	11,976	3_taste_flavor_delicious_sweetness	['taste', 'flavor', 'delicious', 'sweetness', 'flavor', 'not sweet', 'crisp and sweet', 'flavor', 'sour and sweet', 'delicious']
4	6,240	4_worst_disappointing_rubbish_terrible	['worst', 'disappointing', 'rubbish', 'very bad', 'terrible', 'wasteful', 'broken', 'scam', 'bad review', 'very bad']
5	5,681	5_purchased_online_last_year_in-store	['purchase', 'online', 'last year', 'in the store', 'buy', 'after-sales', 'brand', 'countless times', 'enjoyable', 'bought back']
6	5,673	6_children_buying groceries_weight loss_vegetables	['children', 'grocery shopping', 'weight loss', 'vegetables', 'at home', 'food', 'supplementary food', 'appetite', 'food', 'health']
7	4,893	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	4,872	8_last_consumer_refund_after-sales	['last time', 'consumer', 'refund', 'after-sales', 'price reduction', 'one cent', 'regret', 'price', 'shopping', 'don't buy']
9	4,855	9_good review_quality_like_worthy	['good review', 'quality', 'like', 'worthy', 'trustworthy', 'perfect', 'very good', 'praise', 'quite satisfied', 'really good']
10	4,850	10_ratings_comments_support_improvements	['evaluation', 'comment', 'support', 'improvement', 'selection', 'patience', 'activity', 'lessons', 'follow-up review', 'bad review']

Table 5. Continued

Topic	Count	Name	Representation
11	4,399	11_cooking_butter_fried rice cake_rich	[‘cooking’, ‘butter’, ‘fried rice cake’, ‘rich’, ‘delicious’, ‘starch’, ‘a bowl’, ‘noodles’, ‘juice’, ‘winter melon soup’]
12	4,247	12_refrigerator_ice pack_freezing_thawing	[‘refrigerator’, ‘ice pack’, ‘freeze’, ‘thaw’, ‘freeze’, ‘cold chain’, ‘frozen products’, ‘frozen’, ‘temperature’, ‘winter’]
13	4,155	13_cost-effectiveness_cheap_shopping_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	4,073	14_seller_brand_trust_prosperous business	[‘seller’, ‘brand’, ‘trust’, ‘prospering business’, ‘affordable’, ‘shop’, ‘product quality’, ‘value for money’, ‘after-sales service’, ‘customer’]
15	3,935	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	3,082	16_clean_water_boil_hygienic	[‘clean’, ‘water injection’, ‘boil’, ‘hygienic’, ‘clear water’, ‘soak in water’, ‘wash’, ‘medicine’, ‘lots of water’, ‘sand’]
17	1,536	17_jd.com_taobao_mall_logistics	[‘jingdong’, ‘taobao’, ‘mall’, ‘logistics’, ‘shopping’, ‘buying vegetables’, ‘trust’, ‘convenient and fast’, ‘daily necessities’, ‘worthy’]

4.2 Validation of Topic Modeling Outputs

To evaluate the quality of the topic modeling results, three complementary quantitative indicators were employed: topic coherence (C_V), topic diversity, and topic stability.

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Following Röder et al. (2015), topic coherence (C_V) was used to assess the semantic relatedness among the top keywords within each topic. The Gensim CoherenceModel was applied, utilizing the top 10 keywords per topic, a sliding window approach, and normalized pointwise mutual information (NPMI). A higher C_V score indicates stronger semantic consistency and better interpretability of the topic. Generally, C_V values above 0.45 are considered acceptable, indicating a semantically meaningful topic structure.

As described by Dieng et al. (2020), topic diversity was calculated as the proportion of unique words among the top N words across all topics, using the formula:

Topic Diversity = (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, $N = 10$). A higher topic diversity value (typically above 0.90) suggests minimal redundancy of terms across topics and stronger thematic separability.

Table 6. Topic Coherence and Stability Metrics for Each Identified Topic

Topic	**C_V**	**Mean Jaccard**	**SD Jaccard**
0	0.55	0.67	0.05
1	0.54	0.66	0.06
2	0.52	0.64	0.05
3	0.57	0.69	0.04
4	0.48	0.62	0.07
5	0.50	0.63	0.05
6	0.51	0.62	0.06
7	0.56	0.66	0.04
8	0.49	0.61	0.05
9	0.53	0.64	0.06
10	0.50	0.63	0.05
11	0.49	0.60	0.06
12	0.55	0.68	0.04
13	0.52	0.62	0.05
14	0.51	0.61	0.06
15	0.50	0.60	0.06
16	0.49	0.61	0.07
17	0.47	0.62	0.08
Mean	0.52	0.64	—

Following Hoyle et al. (2021), topic stability was assessed via multiple independent runs of the model using different random seeds. For each topic, the top 10 keywords from each run were compared using Jaccard similarity, and both the mean and standard deviation (SD) of these similarity scores were computed. A mean Jaccard above 0.60 combined with an SD below 0.06 indicates that the topic structure is robust and consistently reproduced across runs.

The results show that the topic modeling achieved good semantic coherence, with a mean C_V score of 0.52. The high topic diversity score of 0.94 suggests minimal keyword overlap among topics. Furthermore, the model demonstrated strong stability, with a mean Jaccard similarity of 0.64, indicating consistent topic formation across multiple runs. These results are summarized in Table 6, which presents the values of C_V coherence and Jaccard-based stability metrics.

5. Discussion

To facilitate interpretation and theoretical alignment, the identified topics were grouped into six higher-level service quality dimensions based on their semantic content and relevance. Table 7 summarizes this mapping, showing how each topic cluster corresponds to specific dimensions within established frameworks such as SERVQUAL (Parasuraman et al., 1988) and E-S-QUAL (Parasuraman et al., 2005). In line with prior studies that mapped unsupervised outputs to conceptual service models (Ladhari, 2010), this interpretive step enhances the theoretical relevance of the model results.

Topics describing product attributes such as *freshness*, *taste*, *appearance*, and *size* were grouped under the Product Quality dimension. These attributes reflect tangible aspects of service offerings and correspond to the Tangibles component of the SERVQUAL model. In the context of fresh e-commerce, tangible product features are central to customer evaluations of quality, especially for perishable goods (Pan, 2024; Zhang et al., 2023).

Keywords related to *logistics efficiency*, *cold chain handling*, and *delivery service attitude* were associated with the Logistics & Cold Chain dimension. This aligns with the Fulfillment component in the E-S-QUAL model, which reflects the accuracy, completeness, and timeliness of service execution. For fresh goods, fulfillment also involves maintaining cold-chain reliability and ensuring timely last-mile delivery, making it an essential component of service quality (Blut, 2016; Wang et al., 2024).

Topics focused on *pricing*, *discounts*, and *value for money* were grouped into the Economic Efficiency dimension. This dimension reflects the notion of Perceived Value, which captures the trade-off between cost and benefits and is a known determinant of satisfaction in online services (Cronin Jr et al., 2000; Voss et al., 1998). Perceived value is particularly critical in highly competitive and price-sensitive markets, such as the fresh e-commerce sector (Ling et al., 2023; Ren et al., 2025).

Customer service-related topics, including after-sales support, complaint handling, and brand trust, were categorized under the Customer Service dimension. This corresponds to the Responsiveness dimension in SERVQUAL, which evaluates the firm's willingness and ability to assist customers promptly. In e-commerce, responsiveness also encompasses automated systems, chatbots, and fast resolution processes (Oktavia & Arifin, 2024; Uzoka et al., 2024).

User interaction topics such as *reviews*, *comments*, and *feedback loops* were mapped to the Platform Experience dimension. This dimension aligns with Efficiency in the E-S-QUAL model, referring to the ease and speed with which information can be found and tasks completed online. Interactive features such as user reviews and feedback mechanisms are critical elements of digital service performance and trust-building (Hochstein et al., 2023; Peña-García et al., 2024).

Topics related to *packaging integrity*, *cleanliness*, and *hygiene* were categorized under "Packaging & Hygiene," corresponding to "Reliability" in the SERVQUAL model. Reliability refers to the consistency and dependability of service performance, which in the context of fresh e-commerce includes ensuring that items are clean, properly packed, and undamaged (Jie & Karia, 2024).

Table 7. Dimensions from Topic Modeling with Mapping to Classic SQ

Dimension	**Topics**	**Count (% Total)**	**Representative Keywords**	**SERVQUAL / E-S-QUAL Mapping**
Product Quality	0,1,2,3,6,11	78,697 (60.0%)	Appearance, size, freshness, taste, usage context	Tangibles (SERVQUAL)
Logistics & Cold Chain	7,12,17	10,676 (8.1%)	Delivery speed, logistics service attitude, cold chain	Fulfillment (E-S-QUAL)
Economic Efficiency	8,13	9,027 (6.9%)	Price, price reduction, value for money	Perceived Value (Extended Dimension in E-service Quality)
Customer Service	4,5,14	15,994 (12.2%)	After-sales, complaint handling, brand trust	Responsiveness (SERVQUAL)
Platform Experience	9,10	9,705 (7.4%)	Reviews, comments, feedback	Efficiency (E-S-QUAL)
Packaging & Hygiene	15,16	7,017 (5.4%)	Packaging integrity, cleanliness	Reliability (SERVQUAL)

The mapping of topics into higher-level service quality dimensions further uncovers the dominance of these categories. As shown in Table 7, Product Quality was by far the most prominent dimension, representing 60.0% of all extracted clauses. This indicates that consumers overwhelmingly focus on tangible product features, such as freshness, taste, appearance, and size, when evaluating fresh e-commerce platforms. Customer Service (12.2%) and Logistics & Cold Chain (8.1%) reflected concerns related to complaint handling, brand trust, and delivery reliability. In comparison, Economic Efficiency (6.9%), Platform Experience (7.4%), and Packaging & Hygiene (5.4%) appeared as secondary but still important factors. These findings highlight that, although multiple aspects of service quality matter, consumer discussions are mainly driven by perceptions of product quality, with logistics, service responsiveness, and value for money playing supporting roles.

To better place these findings within the larger body of research, it is helpful to compare the identified dimensions with those found in earlier studies. Lee et al. (2020) and Ma and Li (2020) both highlighted product quality and logistics efficiency as key elements in evaluating fresh e-commerce services, aligning with the current study's finding that Product Quality represented the most significant portion of user discourse. Hou and Wang (2022) highlighted packaging, logistics, and customer care as essential factors, which partly overlap with the Packaging & Hygiene and Customer Service dimensions identified here. However, some differences also appeared. While Chen et al. (2023) found logistics service quality and information quality to be the primary factors derived from online reviews, this study reveals a stronger emphasis on price and value for money, encompassed in the Economic Efficiency dimension. These similarities and differences suggest that although product and logistics aspects are consistently important across studies, the emphasis on cost considerations and platform experience varies according to the specific context of China's highly competitive, price-sensitive fresh e-commerce market.

6. Conclusion

This study utilizes a large-scale dataset of user reviews to ensure that the results reflect genuine consumer experiences. The use of advanced topic modeling introduces a new, data-driven method that reveals the thematic structure of consumer discussions beyond traditional survey techniques. Additionally, focusing on China's fresh e-commerce market provides timely insights into a rapidly growing sector that has received limited academic study.

At the same time, several limitations should be acknowledged. First, relying on online review data means the results reflect expressed opinions, which might not fully capture silent insights or less vocal consumer groups. Second, topic modeling reveals the frequency of themes in user discourse but does not necessarily indicate their causal impact on satisfaction or behavioral outcomes. Finally, the study is specific to China's fresh e-commerce industry, and caution is needed when applying the findings to other countries or retail settings. These limitations underscore the need for future research to employ additional methods and conduct cross-market comparisons to validate and expand upon the conclusions.

This study explored customer perceptions of service quality in China's fresh food e-commerce sector by applying topic modeling to large-scale online reviews and mapping the extracted topics to established frameworks such as SERVQUAL and E-S-QUAL. The analysis identified six core dimensions—Product Quality, Logistics & Cold Chain, Economic Efficiency, Customer Service, Platform Experience, and Packaging & Hygiene—that reflect both classical service quality constructs and domain-specific expectations unique to fresh e-commerce. These findings contribute to the literature by demonstrating how data-driven methods can enrich theoretical models and offer practical guidance for platform improvement. However, several limitations should be noted. The use of unsupervised modeling relies on the interpretability of the extracted topics, and the mapping process involves subjective judgment, despite aligning with established theory. In addition, the dataset was limited to four major Chinese fresh e-commerce platforms, which, while enhancing representativeness, may still constrain generalizability to other cultural or regional contexts. Future research could expand to include cross-platform or cross-national comparisons, incorporate temporal dynamics in customer expectations, or integrate quantitative validation through customer surveys to triangulate findings and enhance the robustness of the results.

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Authors contributions

Han Xiaomei was responsible for data collection, analysis, and drafting the manuscript. Prof. Hamrila Abdul Latif provided guidance on study design and critical revision of the manuscript. Prof. Puah Chin Hong contributed by providing submission guidance and valuable suggestions to improve the paper. All authors read and approved the final manuscript.

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Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Obtained.

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The Publication Ethics Committee of the Macrothink Institute.

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

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No additional data are available.

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