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Identifying Customer Preference Factors in Front-Warehouse Fresh E-commerce: A BERTopic and Sentiment Analysis Approach

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Abstract

In recent years, front-warehouse fresh e-commerce has rapidly expanded in China, with platforms such as Dingdong Maicai meeting consumer demand for high-frequency and immediate grocery purchases through instant delivery. However, the perishability of goods, reliance on cold-chain logistics, and price sensitivity create divergent consumer experiences. Drawing on 14,118 user reviews segmented into 25,297 sentence-level units, this study applies BERTopic to extract themes and employs a RoBERTa-based sentiment classification model to identify polarity. A total of 38 valid topics were identified and consolidated into seven aspects: freshness, taste, packaging, delivery, price, customer service, and image–text mismatch. Results indicate that freshness and packaging are the primary sources of negative sentiment, while price and delivery attract both positive and negative attention. Overall, consumer evaluations are predominantly positive, yet product deterioration, damaged packaging, and inconsistencies between product descriptions and reality elicit notable dissatisfaction. This study not only provides data-driven evidence for understanding consumer preferences but also offers practical implications for platforms to optimize product management and operational decision-making.

Keywords: Front-Warehouse, Fresh e-commerce, Review Mining, BERTopic, Sentiment Analysis

Introduction

With the rise of the "Internet+" initiative, which has accelerated the digital transformation of traditional industries, and the rapid growth of instant retailing, China's instant retail market reached RMB 650 billion in 2023 with a year-over-year growth of 28.9% (Zhang, 2025). In this context, fresh food e-commerce has become one of the most dynamic and important parts of China's digital retail landscape, often highlighted in recent studies as a key area of Internet Plus applications (Ye et al., 2022). Among its innovative formats, the front-warehouse (pre-warehouse) model (Guo et al., 2024) involves strategically placing small warehouses near central business districts or residential communities. By moving the supply chain's endpoint closer to consumers, this model reduces the delivery radius and allows for order fulfillment at the minute level. It effectively solves the "last-mile" bottleneck in traditional central-warehouse-to-home delivery, greatly enhancing delivery speed and customer satisfaction.

Among many platforms, Dingdong Maicai is widely recognized as a prime example of the front-warehouse model. Its business strategy emphasizes "integrated warehousing and distribution combined with community coverage." By placing front warehouses densely around communities, the platform has reduced the delivery radius to approximately three kilometers, allowing fresh food to be delivered within 30 minutes to two hours. This innovation has significantly enhanced user convenience and increased the frequency of purchases. According to iResearch's industry report on China's fresh e-commerce sector, the front-warehouse model has become a mainstream approach, with Dingdong Maicai highlighted as a leading example (iResearch, 2021). Additionally, the company's Form F-1 registration statement, filed with the U.S. Securities and Exchange Commission in 2021, indicated that Dingdong Maicai had established over 950 front warehouses across nearly 30 Chinese cities by the first quarter of 2021 (Dingdong, 2021). Based on its 2024 full-year and fourth-quarter financial reports, the platform added 130 new front warehouses in 2024, surpassing the initial target of 110, while maintaining an average of about 1,000 daily orders per warehouse, reflecting a 22.2% year-over-year increase. In key markets such as Shanghai, the daily order volume per warehouse even exceeded 1,500, well above the national average (Dingdong, 2025). These figures demonstrate that Dingdong Maicai not only leads the industry in warehouse numbers and geographic coverage but also shows strong operational efficiency and fulfillment capacity. Therefore, it serves as an excellent case for studying the front-warehouse model in fresh food e-commerce.

Problem Statement

Front-warehouse fresh e-commerce has emerged as one of the most dynamic and strategically important sectors within China's digital retail landscape. It not only represents an innovation in retail logistics but also plays a pivotal role in the development of the broader digital economy and urban consumption ecosystem. Its rapid growth, coupled with its direct relevance to everyday consumer life, makes it an essential topic of study for both academia and industry.

Despite its promising potential, front-warehouse fresh e-commerce faces significant operational challenges. Fresh products are characterized by high purchase frequency, low transaction value, and rapid perishability, which makes platforms heavily dependent on cold chain logistics, efficient storage, and quick inventory turnover (Harward et al., 2024; Sun et al., 2023). Meanwhile, consumers are increasingly sensitive to factors such as freshness, timely delivery, packaging integrity, and fair pricing. Any negative experience is quickly shared via user reviews, leading to a decline in repeat purchases and user retention (Wang et al., 2024). In an industry characterized by intense competition and extremely narrow profit margins (Ma et al., 2022), these issues are exacerbated and pose a threat to sustainable growth.

A typical example is MissFresh, one of the earliest pioneers of the front-warehouse model. The company went public on the NASDAQ in 2021 with a valuation of nearly USD 3 billion, but it suffered from persistent losses and cash flow crises. Between 2018 and 2021, its accumulated losses exceeded RMB 10 billion. In July 2022, MissFresh abruptly shut down front-warehouse operations in nine cities, including Suzhou, Hangzhou, and Shenzhen, within three days, and later received a delisting warning from NASDAQ due to delayed financial reporting and prolonged stock prices below USD 1 (Produce Report, 2022; TechNode, 2022). This failure highlights the structural vulnerability of the front-warehouse model in conditions of high investment and low margins. More importantly, it reveals a deeper issue: the failure to identify and respond to consumer needs accurately can lead to strategic myopia and blind expansion, ultimately undermining service quality (Levitt, 2004). Moreover, even minor service lapses can trigger customer defection, underscoring the fragility of the consumer-platform relationship (Sands, 2020).

Against this backdrop, understanding and accurately identifying consumers' genuine preferences and pain points has become an urgent research necessity. It provides the foundation for explaining the sustainability of this business model and sets the stage for more systematic investigations into consumer behavior in front-warehouse fresh e-commerce.

User-generated content (UGC) serves as a valuable data source in this context, since online reviews capture consumers' authentic experiences and nuanced perceptions that are often inaccessible through traditional survey-based approaches (Lin et al., 2023; Zhou et al., 2021). With recent advancements in natural language processing (NLP), extracting consumer insights from large-scale text datasets has become more feasible. Specifically, the BERTopic model enables automatic discovery of latent themes by combining embeddings with clustering (Grootendorst, 2022), while deep learning–based sentiment analysis allows for detailed measurement of consumers' emotional orientations (Liu et al., 2023; Zhang et al., 2022).

Research Questions

In this study, Dingdong Maicai, a leading front-warehouse fresh e-commerce platform in China, is selected as the empirical context. Drawing on large-scale user-generated content, advanced topic modeling and sentiment analysis are employed to extract consumer insights. Accordingly, this study seeks to answer two central research questions:
(1) What factors are consumers most concerned about in front-warehouse fresh e-commerce?
(2) What are consumers' sentiment attitudes toward these factors?

Research Significance

From an academic perspective, this research advances the literature in three significant ways. First, previous studies on fresh e-commerce have predominantly relied on consumer surveys or traditional service-quality frameworks, which are constrained by sample size, response bias, and their inability to capture the immediacy and diversity of consumer experiences fully. By contrast, this study leverages large-scale user-generated content (UGC), which reflects spontaneous, real-time consumer opinions and provides richer empirical evidence. Second, while prior topic modeling efforts in this domain have primarily employed Latent Dirichlet Allocation (LDA), such probabilistic models tend to perform poorly with short, fragmented, and colloquial review texts. This study employs BERTopic, an embedding-based neural topic model that incorporates contextual semantic information, thereby significantly enhancing topic coherence and interpretability. Third, although sentiment analysis has been widely applied in e-commerce research, few studies have systematically integrated it with advanced topic modeling to provide a dual perspective—what consumers talk about and how they feel about it. By addressing these gaps, this research contributes both methodological innovation and new theoretical insights into consumer behavior in the context of front-warehouse fresh e-commerce.

From a practical perspective, the study provides actionable insights for various stakeholders. For e-commerce platforms, the findings can guide managers in improving product quality control, optimizing packaging and logistics, and enhancing overall service delivery, thereby reducing negative experiences and building customer loyalty. For consumers, the research indirectly improves their experiences by prompting platforms to respond more effectively to user feedback, which boosts satisfaction and trust. For policymakers and regulators, this study offers empirical evidence to support the development of sustainable, consumer-focused digital retail ecosystems, ensuring fair competition and safeguarding consumer rights in a rapidly growing industry.

Literature Review

The rapid growth of front-warehouse fresh e-commerce in China has driven an increase in academic research. Past studies mainly fall into three categories: (1) analyzing the operational features and challenges of the front-warehouse model; (2) exploring the value of user-generated content (UGC) in understanding consumer perceptions; and (3) applying natural language processing (NLP) techniques, especially topic modeling and sentiment analysis, to gain insights from consumer reviews. However, current research has yet to systematically combine advanced topic modeling and sentiment analysis to examine consumer preferences within the front-warehouse setting, creating a significant research gap.

Front-Warehouse Fresh E-commerce

The front-warehouse model places small warehouses near residential areas to enable “integrated warehousing and distribution” and quick fulfillment. This approach enhances delivery speed and consumer convenience but also brings operational challenges, such as high cold-chain logistics costs, low gross margins, and intense inventory turnover pressures (Xu et al., 2022; Zhou and Xu, 2021). Consumer satisfaction in this model mainly depends on freshness, delivery punctuality, and packaging integrity; service failures directly reduce repurchase intentions (Sun et al., 2023; Wang et al., 2024). Failure cases, such as MissFresh’s withdrawal from U.S. capital markets due to overexpansion and declining service quality, further demonstrate the model’s vulnerability when consumer needs are not adequately met (Harward et al., 2024; Sun et al., 2023). These insights highlight that balancing efficiency, cost control, and consumer satisfaction remains the main challenge for front-warehouse fresh e-commerce.

User-Generated Content (UGC)

UGC, particularly online reviews, has become a crucial data source for understanding consumer behavior in e-commerce. Unlike traditional surveys, UGC is extensive, real-time, and unsolicited, capturing genuine consumer experiences and perceptions (Zhou et al., 2021). UGC highlights detailed consumer concerns about freshness, delivery, service, and price fairness in fresh e-commerce environments (Chen et al., 2022; Lin et al., 2023). Beyond retail, analysis based on UGC is widely applied in tourism, hospitality, and platform economy research, demonstrating its value across various industries (Liu et al., 2023; Zhang and Sun, 2024). Since consumers' experiences in fresh e-commerce are especially sensitive due to product perishability and immediacy, UGC offers an essential resource for identifying key preferences and areas of dissatisfaction.

Topic Modeling

Topic modeling is widely used to find hidden themes in consumer reviews. Traditional models, such as Latent Dirichlet Allocation (LDA), are standard but often struggle with short, sparse texts typical of e-commerce reviews (Wang et al., 2020). Recently, embedding-based methods have become more effective alternatives. For example, BERTopic combines transformer embeddings with clustering and a class-based TF-IDF approach, producing semantically coherent topics even for short texts (Grootendorst, 2022). Comparative studies indicate that embedding-based models outperform traditional topic models in analyzing large-scale consumer reviews and social media data (Lin et al., 2023; Zhao et al., 2023; Guo and Huang, 2024). These advancements make BERTopic particularly useful for identifying preference factors in front-warehouse fresh e-commerce reviews.

Sentiment Analysis

Sentiment analysis is an essential tool for understanding consumer attitudes in online retail. Transformer-based, pre-trained models like BERT and RoBERTa have achieved state-of-the-art results in polarity classification and detailed sentiment detection (Zhang et al., 2022; Liu et al., 2023). In e-commerce, sentiment analysis has been utilized to assess consumer opinions on product quality, delivery speed, pricing fairness, and customer service, all of which are crucial factors in determining satisfaction and encouraging repeat purchases (Chen et al., 2022; Huang and Chen, 2023). Sentiment analysis has also expanded to include multimodal reviews, which combine text and visual data to capture better complex consumer perceptions (Li and Zhang, 2023; Wang and Xu, 2024). When combined with topic modeling, sentiment analysis provides a dual perspective, revealing both what consumers discuss and how they feel about it, thereby offering a comprehensive view of consumer preferences.

Research Gap

Overall, the existing research provides valuable insights into the operational challenges of front-warehouse e-commerce, the usefulness of UGC, and the applications of topic modeling and sentiment analysis. However, three main limitations remain. First, much previous research depends on survey methods or traditional service-quality frameworks, which do not fully capture the variety of consumer experiences in real shopping environments. Second, topic modeling studies mainly use LDA, with limited use of more advanced embedding-based models, such as BERTopic. Third, although sentiment analysis has become more common in analyzing e-commerce reviews, few studies systematically combine topic modeling with deep learning sentiment analysis specifically for front-warehouse fresh e-commerce. To address these gaps, a mixed-method approach that incorporates advanced NLP techniques is needed to identify consumer preference factors and their related sentiment attitudes.

Research Methodology

This study adopts a mixed-method text mining approach that combines topic modeling and sentiment analysis to identify consumer preference factors and their associated attitudes in front-warehouse fresh e-commerce. The methodology comprises four main stages: data collection, data preprocessing, topic modeling, and sentiment analysis.

Data Collection

This study focuses on Dingdong Maicai, a leading front-warehouse fresh e-commerce platform, and examines four main product categories: fruits, vegetables, meat and eggs, and aquatic products. Data collection took place from July 2024 to July 2025, covering a complete seasonal cycle. This approach mitigates potential biases resulting from consumption preferences within a single season. It captures variations throughout the year, which is especially important given the seasonality and immediacy typical in front-warehouse fresh e-commerce.

In terms of product selection, each category features top-selling items to ensure enough review volume and reliable analysis. The fruit category includes apples, oranges, grapes, and cherries; vegetables consist of tomatoes, cucumbers, green peppers, and potatoes; meat and eggs comprise pork, beef, chicken, and eggs; and aquatic products feature grass carp, shrimp, salmon, and shellfish. These choices encompass both everyday necessities with high sales volumes and premium, experience-oriented products, reflecting the diverse needs of consumers across various segments.

During the collection process, all available consumer reviews from product pages were systematically gathered, ensuring that both positive and negative evaluations were included to prevent sentiment bias. Additionally, proportional allocation was applied across categories to stop any single product group from dominating the dataset. A total of 19,167 reviews were collected. This dataset provides comprehensive coverage of Dingdong Maicai’s major fresh product categories, offering sufficient scale and diversity to accurately reflect authentic consumer experiences and evaluations under the front-warehouse model.

Data Preprocessing

After collecting the raw reviews, a multi-layered cleaning and normalization procedure was applied to ensure the reliability of subsequent topic modeling and sentiment analysis. First, invalid records were removed, including missing values, overly short entries, or those consisting only of meaningless symbols. Reviews without Chinese content or with obvious advertising characteristics were also excluded. The remaining texts were standardized by converting full-width characters to half-width characters, applying lowercase, and removing redundant spaces and line breaks.

To mitigate semantic bias resulting from the frequent occurrence of product names, an iterative dictionary-based filtering method was employed. In multiple rounds of refinement, standard product terms like "shrimp," "fish," "beef," and "apple," along with contextually irrelevant words such as "family," "children," and "mother," were systematically eliminated. This ensured that the extracted topics concentrated on experiential aspects—such as freshness, delivery punctuality, packaging, price, and service—rather than being overshadowed by repetitive product names.

Following this step, the reviews were segmented into shorter units to achieve finer-grained analytical resolution. The segmentation relied on natural Chinese punctuation markers, including sentence-ending symbols ("。", "！", "？"), pause markers ("，" and "；"), and ellipses ("……" or "...") that indicate semantic breaks. Whenever such punctuation was detected, it was treated as a potential boundary, and the original review was split into multiple semantically independent clauses.

Through this process, the 14,118 cleaned reviews were further divided into 25,297 short-text units, significantly enhancing the dataset's granularity and enabling the models to capture consumer perceptions across various aspects better. Table 1 shows an example of the preprocessing pipeline. The original review, which often included product names, colloquial expressions, and multiple evaluation points, was first cleaned by removing redundant product references and irrelevant terms while keeping the experiential content. It was then broken into short, semantically independent clauses, each representing a single evaluation dimension (e.g., freshness, price, or delivery).

Table 1
Example of Review Preprocessing

Stage	Text Example	Description
Original review	"苹果真的是太新鲜啦！！比超市便宜，家人都说好吃，不过快递拖了一天才到" (The apples were super fresh!! Cheaper than the supermarket, my family all said it tasted good, but the delivery was delayed by a day)	Contains product name, colloquial expressions, and multiple evaluation points, including freshness, price, family opinions, and delivery.
After cleaning	"真的是太新鲜啦！比超市便宜，不过快递拖了一天才到" (Super fresh! Cheaper than the supermarket, but the delivery was delayed by a day)	Product name ("apples"), redundant symbols, and irrelevant context ("family") removed; experiential content retained.
After segmentation	"真的是太新鲜啦！" (Super fresh!) "比超市便宜" (Cheaper than the supermarket) "快递拖了一天才到" (The delivery was delayed by a day)	Each clause is isolated into an independent unit, ensuring one evaluation point per segment (freshness, price, delivery).

Table 2 presents the distribution of reviews by product category after cleaning. The dataset comprises four main categories of Dingdong Maicai: vegetables, fruits, meat & eggs, and aquatic products. A total of 19,167 raw reviews were collected across these categories, with 14,118 valid and cleaned reviews retained for analysis.

Table 2
Review Data by Product Category

Product Category	Raw Review Data	Cleaned Comment Data
Vegetables	4,346	3,032
Fruits	5,075	3,676
Meat & Eggs	4,639	3,421
Aquatic Products	5,107	3,989
Total	19,167	14,118

Topic Modeling with BERTopic

BERTopic is a neural framework that combines contextual embeddings from pre-trained language models, density-based clustering, and class-based TF-IDF (c-TF-IDF) to produce semantically coherent and interpretable topics from short-text collections (Grootendorst, 2022).

In contrast, the traditional Latent Dirichlet Allocation (LDA) approach relies on the bag-of-words assumption, deriving latent topics solely from word frequency and co-occurrence patterns (Blei et al., 2003). This method often ignores contextual semantic information and tends to perform poorly on short, colloquial, and noisy texts such as e-commerce reviews, resulting in fragmented or ambiguous topics (Zhao et al., 2021; Wang et al., 2020; Albalawi et al., 2020). Embedding-based neural topic models outperform probabilistic methods when extracting coherent themes from online reviews and other short texts (Qiang et al., 2020; Sia et al., 2020).

For semantic representation, this research utilizes the “paraphrase-multilingual-MiniLM-L12-v2” embedding model, a component of the Sentence-Transformers family (Reimers and Gurevych, 2019). This lightweight model supports over 50 languages, including Chinese, and effectively captures semantic equivalence across different expressions (Wang et al., 2021). Compared to larger models like “BERT-base-Chinese”, “paraphrase-multilingual-MiniLM-L12-v2” strikes a better balance between semantic accuracy and computational efficiency, making it suitable for large-scale e-commerce review analysis (Li et al., 2022). For example, expressions like “delivery was slow” and “logistics were delayed” may seem unrelated in LDA but are close in MiniLM’s embedding space, leading to their clustering into the same semantic topic. Next, BERTopic applies a density-based clustering algorithm (Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN)) to group reviews with similar semantics, followed by c-TF-IDF to identify keywords for each cluster. This combination of contextual embeddings and weighted keyword extraction ensures both semantic accuracy and interpretability of the resulting topics (Zhou et al., 2023).

To further improve topic interpretability, the minimum topic size was adjusted to prevent excessive fragmentation and noise. This setup allowed BERTopic to generate a moderate number of semantically consistent topics, providing a solid foundation for subsequent sentiment analysis.

Sentiment Analysis Based on the RoBERTa Model

Sentiment analysis is a key task in natural language processing, aiming to identify subjective emotions or attitudes in text and classify them as positive, negative, or neutral (Liu, 2012). In the context of e-commerce reviews, sentiment analysis is a valuable tool for revealing genuine consumer experiences and perceptions of products and services, supporting further research into customer satisfaction and decision-making.

For this study, the RoBERTa Chinese pre-trained model (uer/roberta-base-finetuned-jd-full-chinese) was used. This model, based on the RoBERTa-Base architecture, was fine-tuned with the UER-py toolkit on large-scale Chinese e-commerce review datasets (Zhao et al., 2019). Unlike general language models, its training data include domain-specific sources such as JD full, JD binary, and Dianping review datasets, which improve its ability to detect sentiment features unique to consumer reviews (Hugging Face, 2025). During training, the model used a maximum input of 512 tokens and was optimized over three epochs, with the best model on the development set retained as the final. Thanks to this targeted fine-tuning, the model outputs three sentiment categories—positive, neutral, and negative—along with confidence scores for each. This enables more accurate sentiment detection and, when combined with consumer preference factors, provides a comprehensive view of sentiment distribution across various aspects, ultimately highlighting areas most likely to generate negative feedback.

Compared to traditional lexicon-based and rule-based methods, RoBERTa shows clear methodological advantages for analyzing e-commerce reviews. Lexicon-based approaches, which depend on predefined sentiment dictionaries and polarity scores, are quick and easy but often misinterpret context, negations, or sarcasm. For example, the phrase “not bad” includes a negative word but expresses a neutral or even positive sentiment—an ambiguity that lexicon methods often misjudge (Taboada et al., 2011). VADER (Valence Aware Dictionary and sEntiment Reasoner) enhances basic lexicon approaches by adding degree adverbs and partial negation handling, proving effective for social media content. However, it still relies mainly on handcrafted rules and struggles with more complex contextual cues and implicit sentiments, especially in Chinese-language reviews (Hutto and Gilbert, 2014). In contrast, RoBERTa employs the Transformer architecture (Liu et al., 2019) and its multi-layer self-attention mechanism to capture long-range dependencies and global semantic relationships, resulting in more accurate and context-aware analysis. The domain-specific RoBERTa model employed here is tailored for e-commerce review data and provides confidence-based outputs, making it uniquely capable of identifying subtle variations in sentiment intensity.

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.

Extracted Topics and Model Evaluation

This study applies BERTopic to extract themes from user reviews on the Dingdong Maicai platform. In the model configuration, the parameter min_topic_size was set to 200. This parameter is derived from the underlying HDBSCAN clustering algorithm, which specifies the minimum number of documents required to form a valid cluster (McInnes et al., 2017). Clusters smaller than this threshold are treated as noise or merged into larger clusters.

The choice of min_topic_size = 200 in this study is grounded in both methodological considerations and the characteristics of the dataset. The segmented corpus used in this study consists of approximately 20,000 sentences. Setting the threshold to 200 (about 1% of the dataset) is sufficiently small to avoid overlooking meaningful patterns, yet large enough to suppress trivial or fragmented clusters. This configuration ensures that each identified topic is supported by an adequate amount of textual evidence, allowing the results to strike a balance between interpretability and representativeness.

The parameter choice enhances the robustness of topic modeling results by minimizing noise, avoiding over-fragmentation, and securing stable topics that are both meaningful and empirically grounded. Moreover, this practice aligns with prior studies that employ BERTopic or HDBSCAN, which emphasize the importance of setting a reasonable minimum topic size to ensure topic stability and interpretability in large-scale text corpora (Angelov et al., 2020; Feng et al., 2025; Eklund et al., 2023).

Under this configuration, the modeling process, which involves text vectorization, dimensionality reduction, clustering, and keyword extraction, identified 29 stable topics. Each cluster was automatically assigned a unique identifier (*Topic_id*) by the algorithm, ensuring that every sentence in the corpus could be unambiguously linked to a specific topic. For visualization, Figure 1 presents a bar chart of the top 10 keywords for each topic, allowing for intuitive recognition of their semantic emphasis, and is complemented by brief explanatory notes.

To assess the validity of the topic modeling results, this study employed two widely used evaluation metrics: topic diversity (measured as topic diversity@N) and inter-topic mean similarity (Dieng et al., 2020; Angelov, 2020). Topic diversity evaluates the lexical distinctiveness across topics. It is calculated by taking the union of the top N keywords from all topics and dividing the number of unique keywords by the total number of keywords considered ($N \times K$, where K is the number of topics). A value closer to 1 indicates that the topics rely on vastly different sets of representative words, suggesting low redundancy and high differentiation in the learned topics. Inter-topic mean similarity, by contrast, measures the semantic relatedness of topics in the embedding space. Each topic is represented by an embedding vector, typically derived from the centroid of document embeddings within that topic. The cosine similarity between all possible topic pairs is computed, and the average of these values is taken as the metric. Lower values indicate that topics are more distinct from each other, while higher values imply more substantial semantic overlap among topics.

In this study, the results show topic diversity@5 = 0.9241 and topic diversity@10 = 0.8621, demonstrating that the identified topics exhibit a high degree of lexical heterogeneity in their top-ranked keywords. The inter-topic mean similarity was found to be 0.4031, suggesting that although the topics are generally well-separated, specific pairs display relatively close semantic proximity, indicating possible opportunities for merging or refinement in subsequent analysis.

Mapping Topics onto Consumer Concern Aspects

The output of topic modeling algorithms typically manifests as clusters of keywords and their associated semantic groupings. These results require interpretive efforts by researchers to reveal the substantive consumer concerns they represent. In the social sciences and communication research, topic models are frequently applied in conjunction with manual interpretation and classification of topics based on contextual and semantic features (Maier et al., 2018; Jacobi et al., 2016).

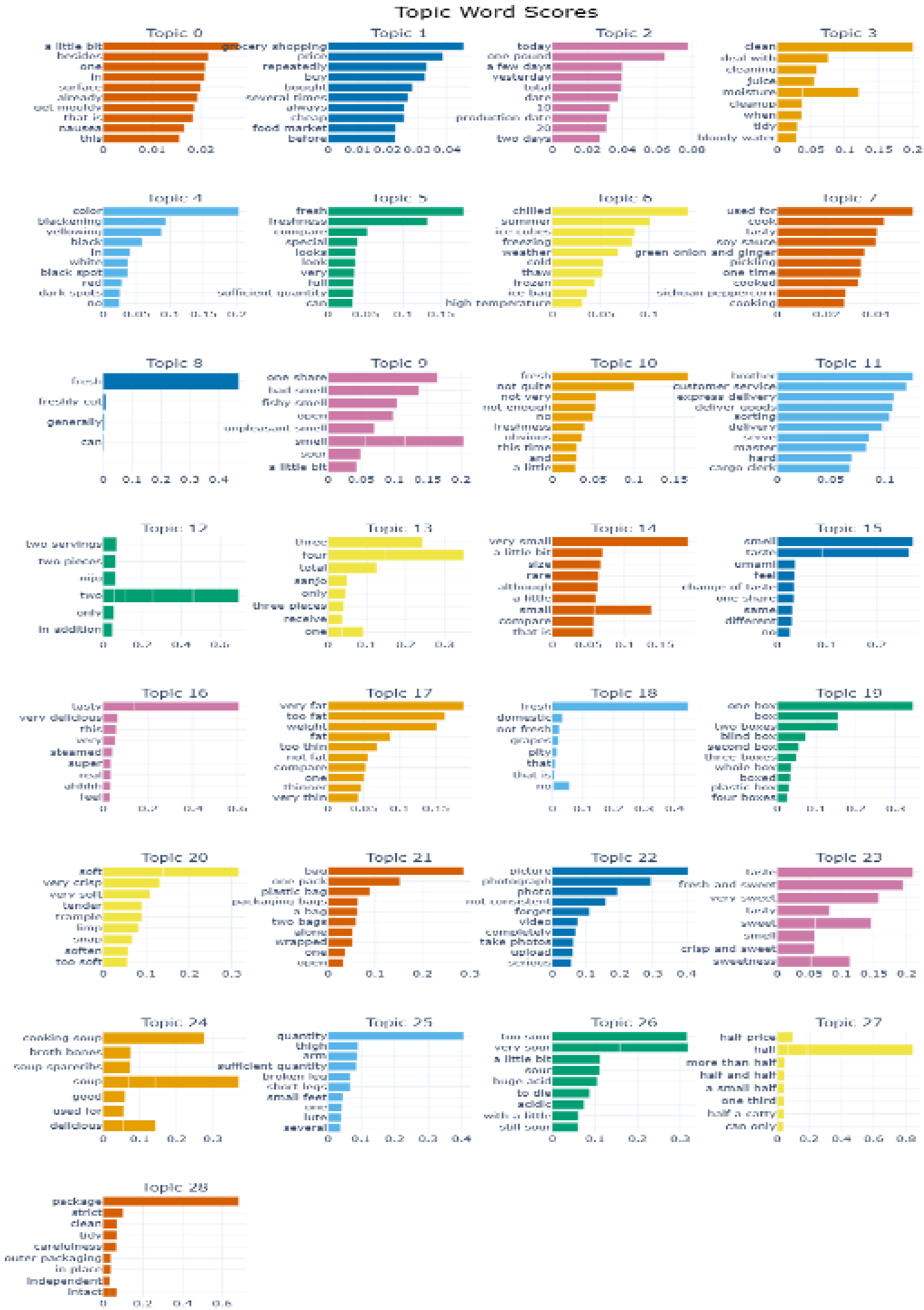

Figure 1. Top 10 Keywords for Each Identified Topic

In this study, a combined approach of manual semantic matching and expert validation was employed. First, researchers examined the high-frequency keywords and representative comments of each topic to determine its underlying consumer concern. Two researchers then independently assigned topics to candidate categories, and disagreements were resolved through discussion to enhance reliability and consistency. Each sentence segment, having already been assigned a unique Topic_id during the BERTopic clustering process, thereby inherits this identifier when mapped to its corresponding consumer concern aspect. This ensures that sentiment analysis in the next stage can be conducted not only at the topic level but also aggregated by aspect. As a result, the 29 identified topics were consolidated into seven consumer concern dimensions, namely freshness, taste, price, packaging, delivery, quantity, and image–text mismatch, as illustrated in Table 3.

Table 3
Mapping of Extracted Topics to Consumer Concern Aspects

Aspect	Topic_id	Count	Representative Words
Freshness	0	4103 (18.90%)	'a little bit', 'also', 'one', 'inside', 'surface', 'already', 'moldy', 'that', 'disgusting', 'this'
	2	2002 (9.22%)	today','one pound','a few days','yesterday','total','date','10','production date','20','two days'
	4	819 (3.77%)	'color', 'black', 'yellow', 'black', 'inside', 'white', 'black spots', 'red', 'black spots', 'not'
	5	792 (3.65%)	'fresh', 'freshness', 'relatively', 'special', 'looks', 'looks', 'very', 'full', 'sufficient', 'ok'
	8	687 (3.17%)	'fresh', 'freshly cut', 'average', 'ok'
	9	656 (3.02%)	'a smell', 'stink', 'fishy smell', 'open', 'stinky', 'peculiar smell', 'taste', 'smelly smell', 'sour smell', 'a little bit'
	10	566 (2.61%)	'fresh', 'not quite', 'not quite', 'not enough', 'not', 'freshness', 'obviously', 'this time', 'and', 'a little'
	18	287 (1.32%)	'fresh', 'not', 'domestic', 'not fresh', 'grapes', 'what a pity', 'that kind', 'just', 'no'
Price	1	3800 (17.51%)	'buy groceries', 'price', 'many times', 'buy', 'bought', 'several times', 'always', 'cheap', 'vegetable market', 'before'
Taste	7	725 (3.34%)	'use', 'cooking', 'delicious', 'soy sauce', 'scallion and ginger', 'pickle', 'for a while', 'cooked', 'peppercorn', 'cooking'
	15	413 (1.90%)	'taste', 'mouthfeel', 'flavor', 'umami', 'feel', 'changed taste', 'a smell', 'same', 'different', 'no'
	16	369 (1.70%)	'delicious', 'yummy', 'very delicious', 'this', 'very', 'steamed', 'super', 'really', 'ahhh', 'feel'
	17	367 (1.69%)	'very fat', 'too fat', 'weight', 'fat', 'too thin', 'not fat', 'relatively', 'one', 'thinner', 'very thin'
	20	278 (1.28%)	'soft', 'soft', 'very crisp', 'very soft', 'tender', 'tap', 'soft', 'pop', 'softened', 'too soft'
	23	242 (1.11%)	'taste', 'fresh and sweet', 'very sweet', 'sweet', 'delicious', 'sweetness', 'light and sweet', 'taste', 'crisp and sweet', 'sweetness'
	24	233 (1.07%)	'boil soup', 'make soup', 'delicious', 'soup bones', 'soup spareribs', 'soup juice', 'in the soup', 'good', 'used for', 'delicious'
	26	226 (1.04%)	'too sour', 'very sour', 'very sour', 'a little', 'sour', 'very sour', 'too deadly', 'slightly sour', 'a little sour', 'still sour'

Quantity	12	489 (2.25%)	'two', 'two', 'two strips', 'two portions', 'two pieces', 'two strips', 'two', 'only', 'in addition'
	13	488 (2.25%)	'three', 'four', 'four', 'a total', 'one', 'three', 'only', 'three pieces', 'received', 'one'
	14	446 (2.05%)	'very small', 'tiny', 'a little bit', 'size', 'very little', 'although', 'a little', 'tiny', 'relatively', 'just'
	19	282 (1.30%)	'one box', 'box', 'two boxes', 'blind box', 'two boxes', 'three boxes', 'whole box', 'boxed', 'plastic box', 'four boxes'
	25	227 (1.05%)	'weight', 'thigh', 'arm', 'sufficient amount', 'broken leg', 'short leg', 'bound foot', 'one', 'pipa', 'several'
	27	214 (0.99%)	'half', 'half', 'half price', 'half', 'more than half', 'half and half', 'a little half', 'one third', 'half a catty', 'only'
Packaging	3	994 (4.58%)	'clean', 'water', 'process', 'clean', 'juice', 'water', 'clean', 'time', 'tidy', 'blood'
	21	274 (1.26%)	'bag', 'a package', 'plastic bag', 'packaging bag', 'one bag', 'two bags', 'separately', 'packaged', 'one', 'open'
	28	203 (0.94%)	'packaging', 'strict', 'clean', 'tidy', 'careful', 'outer packaging', 'in place', 'intact', 'independent', 'intact'
Delivery	6	734 (3.38%)	'fresh', 'summer', 'ice', 'frozen', 'weather', 'fresh', 'thawed', 'frozen', 'ice pack', 'high temperature'
	11	544 (2.51%)	'brother', 'customer service', 'express delivery', 'delivery', 'sorting', 'distribution', 'service', 'master', 'hard work', 'salesman'
Image–text mismatch	22	245 (1.13%)	'picture', 'photo', 'inconsistent', 'forgot', 'video', 'complete', 'take photo', 'upload', 'serious'

To validate the correspondence between the extracted topics and the predefined aspects of consumer concern, this study employed a semantic similarity approach. Topic and aspect embeddings were generated using a pre-trained language model, and cosine similarity was calculated to assess their proximity in semantic space. Higher similarity values indicate more substantial alignment between a topic and a given aspect.

The results demonstrate that each topic achieved its highest similarity score with one specific aspect, which was then identified as its best-matched category (see Table 4). For instance, Topic 0 scored highest on Freshness (0.605); Topic 15 and Topic 16 scored highest on Taste (0.721 and 0.716, respectively); while Topic 11 and Topic 22 corresponded most closely to Delivery (0.662) and Image–text mismatch (0.745), respectively.

Table 4
Validation of Topic-to-Aspect Mapping Using Cosine Similarity Scores

Topic_id	Freshness	Taste	Packaging	Delivery	Price	Image–text mismatch	Quantity
0	**0.605**	0.457	0.518	0.258	0.344	0.280	0.312
1	0.356	0.363	0.222	0.330	**0.454**	0.112	0.278
2	**0.405**	0.268	0.204	0.172	0.138	0.007	0.176
3	0.434	0.448	**0.454**	0.250	0.360	0.193	0.283
4	**0.418**	0.362	0.088	0.051	0.099	0.313	0.212
5	**0.587**	0.415	0.287	0.240	0.391	0.291	0.248
6	0.322	0.400	0.293	**0.431**	0.354	0.131	0.265
7	0.388	**0.440**	0.366	0.190	0.137	0.109	0.199
8	**0.603**	0.446	0.326	0.325	0.415	0.270	0.272
9	**0.643**	0.588	0.384	0.210	0.289	0.186	0.258
10	**0.532**	0.317	0.368	0.212	0.429	0.260	0.258
11	0.365	0.320	0.379	**0.662**	0.499	0.104	0.444

12	0.476	0.465	0.412	0.198	0.333	0.245	**0.542**
13	0.304	0.322	0.325	0.299	0.283	0.192	**0.603**
14	0.359	0.334	0.321	0.190	0.263	0.234	**0.414**
15	0.618	**0.721**	0.329	0.167	0.310	0.199	0.240
16	0.472	**0.716**	0.174	0.188	0.354	0.171	0.227
17	0.337	**0.419**	0.212	0.132	0.352	0.161	0.365
18	**0.695**	0.475	0.443	0.272	0.417	0.315	0.239
19	0.351	0.422	0.389	0.346	0.411	0.193	**0.664**
20	0.497	**0.593**	0.421	0.274	0.384	0.264	0.405
21	0.264	0.274	**0.535**	0.328	0.371	0.153	0.528
22	0.366	0.366	0.368	0.175	0.286	**0.745**	0.275
23	0.555	**0.824**	0.223	0.230	0.393	0.255	0.303
24	0.414	**0.478**	0.317	0.224	0.266	0.096	0.272
25	0.243	0.274	0.330	0.312	0.321	0.200	**0.605**
26	0.524	**0.561**	0.420	0.149	0.329	0.209	0.205
27	0.479	0.481	0.374	0.210	0.267	0.163	**0.508**
28	0.408	0.459	**0.500**	0.352	0.470	0.294	0.456

Table 3 presents the mapping of topics extracted by BERTopic to consumer concern aspects. Each row corresponds to a specific topic, indicating its assigned aspect, topic identifier (Topic_id), the number of sentence segments associated with the topic and their proportion in the overall corpus (Count), as well as the top ten representative keywords (TopWords).

In terms of overall distribution, topics related to freshness make up the largest share, accounting for 45.6% (9,912 sentence segments), which shows that consumers are highly concerned about product quality and preservation. Price-related topics account for 17.5% (3,800 sentence segments), highlighting the significant role of price in purchase decisions. Taste accounts for 13.1% (2,853 sentence segments), indicating that flavor experience is significant to consumers. Quantity makes up 9.8% (2,146 sentence segments), suggesting that consumers pay close attention to weight and portion size. Packaging accounts for 6.8% (1,471 sentence segments), mainly related to cleanliness and protecting the product. Delivery accounts for 5.9% (1,278 sentence segments), highlighting the importance of timeliness and cold-chain reliability. Lastly, image–text mismatch is only 1.1% (245 sentence segments), but it highlights consumers' sensitivity to discrepancies between product descriptions and the items they actually receive.

Sentiment Analysis Results

After topic modeling and aspect mapping, each review sentence was assigned a unique Topic_id and linked to a corresponding consumer concern aspect. This structure enabled sentiment analysis to be conducted at the aspect level, allowing systematic comparison across different dimensions.

Sentiment classification was conducted using the uer/roberta-base-finetuned-jd-full-chinese model, available from Hugging Face, which is built upon the open-source pre-training framework (Zhao et al., 2019). Since the model is fine-tuned on large-scale Chinese e-commerce reviews, it is particularly suitable for the current study. The model outputs 1–5 star ratings, which were further categorized into three sentiment polarities: ratings of 1–2 stars were classified as Negative, 3 stars as Neutral, and 4–5 stars as Positive. This star-to-polarity conversion is a well-established approach in online review analysis, supported by studies such as Sharma (2021). Figure 2 illustrates the sentiment distribution across aspects.

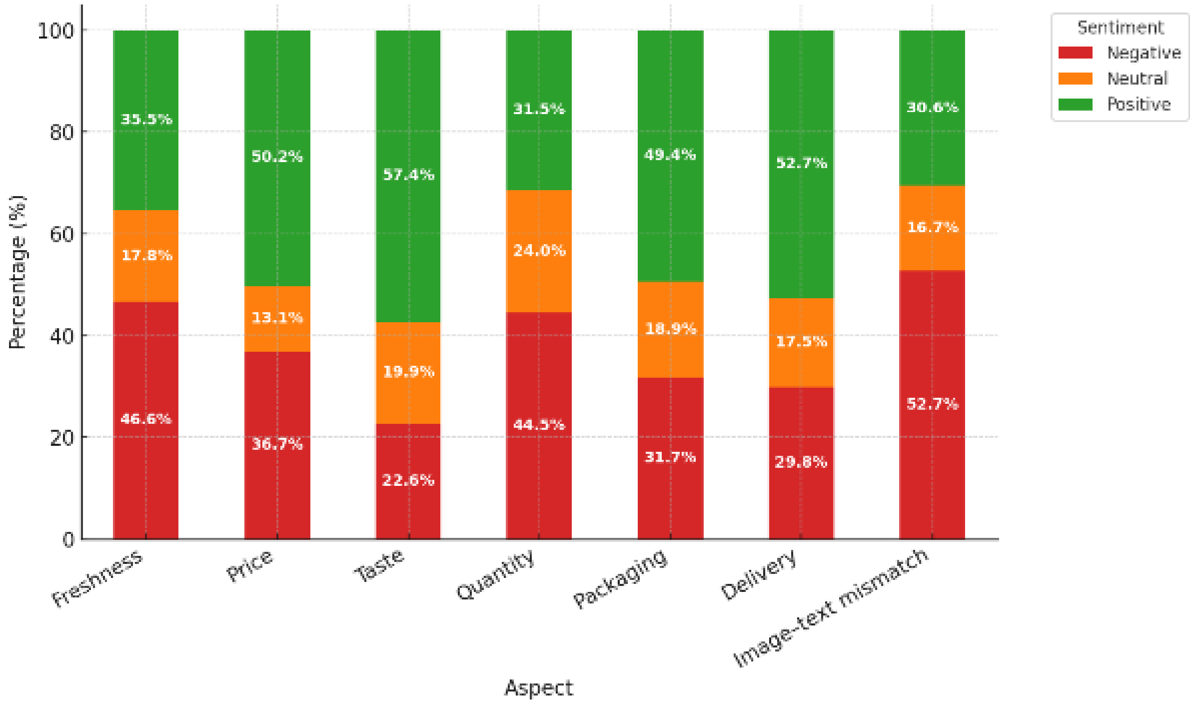

Figure 2. Sentiment Distribution across Aspects

Freshness (9,912 sentences): Negative 4,623 (46.6%), Neutral 1,767 (17.8%), Positive 3,522 (35.5%). Freshness not only attracted the most significant number of comments but also concentrated the highest share of negative feedback, consistent with prior findings that perceived product quality and freshness are critical drivers of satisfaction and trust in fresh food e-commerce (Chen et al., 2023; Yang et al., 2024).

Price (3,800 sentences): Negative 1,396 (36.7%), Neutral 497 (13.1%), Positive 1,907 (50.2%). Results show a polarization between positive assessments of affordability and negative views of expensiveness.

Taste (2,853 sentences): Negative 646 (22.6%), Neutral 569 (19.9%), Positive 1,638 (57.4%). Most comments emphasized positive flavor expressions, such as "delicious" and "fresh," although negative remarks, including "too sour" or "too salty," remained salient.

Quantity (2,146 sentences): Negative 954 (44.5%), Neutral 515 (24.0%), Positive 677 (31.5%). Negative evaluations were primarily concerned with insufficient weight or portion size.

Packaging (1,471 sentences): Negative 466 (31.7%), Neutral 278 (18.9%), Positive 727 (49.4%). While many consumers praised clean and intact packaging, a substantial proportion complained about damage and leakage.

Delivery (1,278 sentences): Negative 381 (29.8%), Neutral 224 (17.5%), Positive 673 (52.7%). Most consumers valued timely delivery and proper cold-chain practices (e.g., use of ice packs), although delays and untimely distribution were recurring complaints, consistent with the literature emphasizing logistics service quality as a determinant of e-commerce satisfaction (Chen et al., 2023; Yang et al., 2024).

Image–text mismatch (245 sentences): Negative 129 (52.7%), Neutral 41 (16.7%), Positive 75 (30.6%). Although the frequency of comments is low, the majority expressed negative sentiment, indicating that even infrequent inconsistencies between product descriptions and actual items strongly undermine user experience. This observation aligns with experimental evidence that image–text inconsistency reduces processing fluency and lowers product evaluations (Lee, 2019).

In summary, sentiment analysis reveals differentiated consumer attitudes across aspects. Product attributes (freshness, price, taste, and quantity) were the core sources of emotional responses, with freshness and quantity most prone to negative sentiment. Service-related aspects (packaging, delivery, and image–text consistency) also played an essential role in shaping satisfaction and trust, with image–text mismatch representing a low-frequency but high-impact risk factor.

Discussion

This study provides new evidence on consumer evaluations in the context of front-warehouse fresh e-commerce. Among all aspects, freshness emerged as the most salient concern, accounting for nearly half of the segmented review sentences and attracting the highest share of negative sentiment. This result underscores the decisive role of product quality and preservation in shaping satisfaction and trust, consistent with prior research that highlights freshness as a cornerstone of the consumer experience in online grocery shopping (Chen et al., 2023; Yang et al., 2024).

Price and taste also proved highly influential but displayed ambivalent consumer attitudes. On the one hand, affordability was frequently praised, while on the other hand, perceptions of “overpricing” triggered dissatisfaction. Taste received predominantly positive evaluations, with descriptors such as “delicious” and “fresh,” though complaints about “too salty” or “too sour” were also evident. These findings align with studies showing that both utilitarian value (e.g., economic efficiency) and hedonic enjoyment (e.g., flavor) jointly shape loyalty and repurchase behavior in online retail (Sharma, 2021).

Beyond these primary attributes, other dimensions showed differentiated patterns of consumer concern. Quantity received a disproportionately high level of negative feedback (44.5%), with repeated references to inadequate weight or portion size. Recent research confirms that quantity shortfalls in perishable goods undermine perceived fairness and reduce repurchase intentions, particularly in contexts where consumers closely monitor transaction transparency (Bharati, 2025). Similarly, packaging and delivery were generally evaluated positively—keywords such as “clean,” “tidy,” and “on time” were dominant—but persistent complaints about damage, leakage, and delays highlighted ongoing vulnerabilities in logistics performance. These results reinforce evidence that logistics service quality has a decisive impact on customer satisfaction and loyalty in fresh food e-commerce (Wang, 2024).

Image–text mismatch, though relatively infrequent at only 1.1% of reviews, exhibited the highest proportion of negative sentiment (>50%). This indicates that visual–textual inconsistencies represent a low-frequency but high-impact risk, capable of severely undermining consumer trust. Experimental research demonstrates that inconsistencies between images and textual descriptions reduce processing fluency and subsequently lower product evaluations (Lee, 2019).

These findings suggest that consumers in front-warehouse fresh e-commerce primarily prioritize freshness, price, and taste, while still paying close attention to quantity, packaging, delivery, and image–text consistency. Each factor exerts a distinct emotional impact, with some (e.g., freshness, quantity) triggering strong dissatisfaction when expectations are not met. In contrast, others (e.g., packaging, delivery) contribute to positive experiences but remain vulnerable to lapses. This multidimensional pattern underscores the value of combining topic modeling and sentiment analysis to capture both the breadth and depth of consumer attitudes in large-scale user-generated content (Zhao et al., 2019).

Conclusion

This study systematically analyzed 21,705 sentence-level reviews of the Dingdong Maicai platform. Using BERTopic, 29 topics were extracted and consolidated into seven aspects: freshness, price, taste, quantity, packaging, delivery, and image–text mismatch. Combined with deep learning–based sentiment analysis, the study addressed two central questions: What factors are consumers most concerned about in front-warehouse fresh e-commerce, and what sentiment attitudes do they hold toward these factors?

The results show that freshness is the most salient consumer concern and also the primary source of negative sentiment. Price and taste exhibited pronounced polarity, with both strong positive and negative evaluations. Quantity issues highlighted consumers' heightened sensitivity to fairness in measurement, while packaging and delivery, though primarily evaluated positively, still generated recurring negative feedback. Image–text mismatch, though low in frequency, displayed a disproportionately high share of negative sentiment, indicating its amplified impact on platform satisfaction and trust.

These findings provide new insights into consumer behavior under the front-warehouse model, underscoring the need for platforms to ensure freshness and transparency in quantity, while also improving packaging and delivery practices and maintaining strict consistency between product images and descriptions. Methodologically, the study demonstrates the feasibility and value of combining topic modeling and sentiment analysis in analyzing e-commerce reviews, as it reveals not only macro-level areas of concern but also fine-grained variations in consumer attitudes. Future research could extend this work in two directions: horizontally, by comparing consumer preferences across different fresh food e-commerce platforms to uncover heterogeneity, and longitudinally, by examining the evolution of consumer sentiment to track how platform adjustments affect user experience over time.

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