Charting the path to consumer satisfaction: An innovative investigation into fresh e-commerce through text mining and spatiotemporal analysis

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Abstract: *The rapid expansion of fresh food e-commerce introduces significant challenges in logistics service quality due to the perishability of products. However, the effects of these challenges on customer satisfaction, particularly across different regions and seasons, have been insufficiently explored. This study addresses this gap by analyzing Jingdong (JD)'s e-commerce reviews using latent dirichlet allocation (LDA) topic models to extract dimensions of logistics service quality, combined with sentiment analysis to evaluate both service quality and customer satisfaction. The research investigates how logistics service quality influences satisfaction, accounting for spatial and temporal variations. Key findings reveal that logistics attributes such as quality assurance, reliability, and convenience play a crucial role in shaping customer satisfaction, with their relative importance differing by region and season. For example, convenience is more critical in remote areas, whereas affluent regions place greater emphasis on empathy. Additionally, higher temperatures amplify the impact of logistics attributes. Repeat customers tend to demand higher service quality compared to first-time buyers. These insights provide actionable recommendations for e-commerce firms seeking to optimize logistics services and enhance their competitiveness.*

Keywords: *Fresh food e-commerce, service quality, online reviews, text mining, customer satisfaction.*

JEL Classification: *M11, P36, Q21.*

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Introduction

With the e-commerce industry's evolution and cold chain logistics technology's ongoing advancement, fresh food e-commerce has garnered increasing consumer interest due to its convenience, efficiency, and diverse offerings. It has emerged as a significant component of China's burgeoning new economy and industry, attracting scholarly attention and serving as a focal point of discussion in the post-epidemic era (Beckers et al., 2021; Han et al., 2022; Mortimer et al., 2024; Shi & Li, 2023; Tsang et al., 2021). The perishable and delicate nature of fresh products underscores the critical role of service quality in ensuring customer satisfaction within fresh food e-commerce (Lin et al., 2021; Liu et al., 2023; Ma et al., 2021). Factors such as inadequate packaging during distribution, subpar storage conditions, delayed deliveries, and improper handling by staff can lead to quality deterioration and consumer discontent. Consequently, the fresh food e-commerce sector imposes higher demands compared to other industries in terms of standardized logistics and distribution management, infrastructure, and workforce quality (Palese & Usai, 2018). Furthermore, China's vast territory and regional economic disparities, coupled with varying geographical conditions, pose challenges to fresh food logistics services, alongside diverse consumer demands and expectations (Haley, 2002; Ji et al., 2024). Hence, fresh food e-commerce enterprises must comprehend and adapt to these disparities to enhance service quality effectively.

In the past, prominent e-commerce platforms refrained from disclosing users' internet protocol (IP) information to uphold consumer privacy standards, resulting in limited spatial exploration within e-commerce services. The exploration of geography and e-commerce is mostly based on survey data (Qian & Chen, 2023; Zhao et al., 2019). However, a notable shift occurred in March 2023, driven by initiatives to foster an environmentally conscious online environment. The JD e-commerce platform commenced displaying IP addresses of reviewing users on product review pages, in compliance with regulations issued by the Cyberspace Administration of China. This initiative lays the groundwork for extensive research endeavors, enabling scholars to utilize review data to investigate regional disparities.

On the other hand, seasonal variations pose distinct challenges for logistics services in the fresh food e-commerce domain, primarily due to the perishability of fresh products and the stringent requirements for storage temperature in different seasons (Steinker et al., 2017; Yin et al., 2023). Consequently, examining the influence of temporal fluctuations on consumers' logistics service demands through a seasonal lens holds significant implications. Such analysis facilitates the adoption of tailored logistics strategies by fresh food e-commerce enterprises, aligning with seasonal variations to enhance overall service quality and responsiveness.

This paper mainly contributes to the exploration of the impacts and fluctuations induced by varying transportation distances, economic disparities, and seasonal variations on consumer demand within the fresh food e-commerce sector. It aims to offer tailored logistics service recommendations to fresh food e-commerce enterprises, thereby augmenting customer satisfaction levels. Specifically, we select JD Fresh as an example, employing an analysis of online comments to dissect the intricacies of fresh food e-commerce service quality from the vantage point of consumer demand. Furthermore, leveraging IP address and date information extracted from comments, we delve into the distinct demand characteristics across different regions and seasons, thus furnishing pertinent suggestions for fresh food e-commerce enterprises to refine their logistics services in a targeted manner. This approach aims to bolster their capacity to efficiently address consumer needs and bolster their competitiveness within the marketplace.

The remainder of this paper is organized as follows: Section 1 presents the research background, reviewing existing research on fresh e-commerce, customer satisfaction and corresponding methodologies. Section 2 explains the whole process and proposed approach. Section 3 empirically analyzes the impact of fresh food e-commerce service quality on customer satisfaction and explores the heterogeneity of new and existing customers based on different number of purchases. The final section summarizes conclusions, implications and limitations for this work.

1. Theoretical background

1.1 Fresh food e-commerce

The fresh food e-commerce sector has witnessed over a decade of evolution, mainly focusing on operational models, supply chain management, and logistics and distribution.

In terms of operational models, Tontini and Silen (2017) used the "punishment-reward" contrast analysis to argue that safety, fault recovery, speed, communication, flexibility, reliability, and friendliness constitute the framework of the logistics service quality model. Meanwhile, Yang et al. (2022) investigated factors shaping satisfaction in fresh produce e-commerce, employing latent dirichlet allocation (LDA) to validate the reassuring influence of e-commerce services amidst the COVID-19.

In terms of supply chain management, Song and He (2018) examined optimal decision-making in centralized and decentralized channels using a three-layer FAP supply chain game theory model encompassing fresh agricultural products e-commerce firms, community convenience stores, and third-party logistics providers. Yang and Tang (2019) conducted a comparative analysis of various sales modes within the fresh produce supply chain using the supplier-retailer Stackelberg model.

In terms of logistics and distribution, Wang et al. (2022) formulated a mathematical model aimed at minimizing time-window penalty costs and mileage segment-based distribution expenses, thereby enhancing distribution efficiency and reducing operational costs for fresh produce sales enterprises. Yang et al. (2024) employed perceptual engineering to emotionally design fresh e-commerce logistics services, catering to the implicit needs of fresh produce consumers. Zahran (2024) tackled the time dependent vehicle routing problem (TDVRP) problem in fresh e-commerce delivery, proposing a method that can effectively avoid the time period of traffic congestion, reduce the total distribution cost, and promote energy saving and emission reduction.

The above studies have made bottleneck breakthroughs for the difficult problems of fresh food e-commerce, while they are largely based on different kinds of operations or game models, and lack of empirical studies based on the consumer perspective that are closer to reality. Although there are a handful of studies on the online shopping scenarios, they have ignored the spatial and temporal perspectives, which do matter for perishable fresh products.

1.2 Service quality

Research on service quality often centers on evaluating it, frequently employing the service quality (SERVQUAL) model (Parasuraman et al., 1998). However, Mentzer et al. (1999) argued that the traditional SERVQUAL model, designed for process-oriented services, may not fully apply to result-oriented logistics services. Thus, they propose the LSQ model, adapting SERVQUAL to suit logistics service characteristics.

Numerous scholars have conducted empirical studies based on the SERVQUAL and LSQ models. Zhang and Hou (2013) used the Cronbach-alpha methodology to gauge the gap between customer expectations and perceptions, examining SERVQUAL dimensions' impact on supply chain service quality. Limbourg et al. (2016) utilized the SERVQUAL scale to assess service quality in logistics companies, identifying deficiencies in transportation and claims handling, necessitating greater attention. Classical service quality theories, while foundational, may not universally apply, prompting scholars to adapt and propose tailored evaluation methods. Yang et al. (2024) gleaned consumer insights from fresh food reviews, constructing service quality indicators for fresh food e-commerce. Yang and Huang (2024) verified that empathy strategies in service quality can awaken consumer forgiveness from service remediation.

These studies provide a theoretical rationale for fine-tuning on the classical service quality models and we will explore the service insights with grounded method based on online reviews.

1.3 Customer satisfaction and text mining based on online reviews

Customer satisfaction is recognized as a key to business performance as well as sustainable growth. Scholars have quested potential influences on the impact of satisfaction from various perspectives and have confirmed its importance. Anderson et al. (1994) underscored the direct impact of service quality on customer satisfaction, indicating its implications for firm performance and profitability. Lim et al. (2021) discovered through text mining and regression analysis that fresh food consumers care about speed, price, cold chain transportation, packaging, quality, error handling, service staff, and logistics information. Gao (2021) analyzed fresh food e-commerce logistics, emphasizing factors enhancing service satisfaction and proposing risk management strategies. However, with the development of the Internet and big data, it is difficult for merchants and researchers to use traditional survey methods such as questionnaires and interviews. Text mining techniques based on online reviews have advantages over traditional survey methods in terms of data volume, objective results, and lower acquisition costs. Thus, they are used by scholars for customer satisfaction. Calheiros et al. (2017) used the LDA model to classify hotel consumer emotions, and found that hotel cuisine can lead to general positive emotions, while hospitality not only brings general positive attitudes but also strong positive attitudes. Wang et al. (2021) utilized TF-IDF and *K*-means algorithms to extract and cluster keywords from hotel reviews, identifying 10 satisfaction factors. Yang et al. (2024) integrated kansei engineering and text mining to delve into dynamic fresh food consumer needs, analyzing satisfaction factors through the implicit demand lens. These studies illustrate the feasibility of utilizing text mining based on online reviews to improve customer satisfaction and provide a set of analytical processes to build upon.

In summary, while existing research provides insights into service quality, subjective methods prevail, prompting the call for more objective approaches considering spatial and temporal dynamics. Leveraging text mining techniques from online reviews, this study aims to quantify service quality and satisfaction, while also exploring spatial and temporal influences, enriching the research landscape in fresh food e-commerce logistics.

2. Research methodology

2.1 Feature extraction for service quality of fresh e-commerce

In this paper, we apply LDA to user comments extracted from the JD Fresh platform, in conjunction with existing literature, to categorize and name dimensions representing evaluation indicators for fresh food e-commerce service quality. Subsequently, we construct a sentiment dictionary and calculate sentiment scores for each dimension, transforming textual data into numerical vector representations. For customer satisfaction measurement, we utilize additional crawled reviews labeled as “good” or “bad” from various e-commerce platforms as samples. Each review’s expression is vectorized via Word2vec, and a SVM model is introduced for high-dimensional semantics classification training. The trained model predicts user satisfaction by embedding their JD Fresh platform reviews and, when combined with the distributed expression vector of evaluation indicators, allows exploration of different dimension impacts on user satisfaction.

2.2 Online review data collection and preprocessing

As a prominent fresh food e-commerce platform, JD Fresh’s user evaluation data derive from actual product purchasers. These reviews encompass diverse aspects of the purchasing process, including product quality, logistics, and after-sales experiences. Public user information such as IP address and release time provides comprehensive data.

JD Mall stores are categorized into self-supporting and non-self-supporting entities. Self-supporting store shipment warehouses are relatively stable, facilitating logistics distance calculations. Consequently, we selected product reviews with the JD self-supporting logo for crawling.

Tab. 1: Classification of fresh food product selection

Category	Product
Fruits (17 kinds from 45 pages)	Cheerios, apples, oranges, coconut green, kiwi fruit, strawberries, pears, durian, blueberries, dragon fruit, cantaloupe, grapes, tangerines, grapefruit, lemons, passion fruit, watermelon
Vegetables (18 kinds from 28 pages)	Oilseed rape, broccoli, spinach, lettuce, pineapple, Chinese cabbage, oatmeal, corn, yams, sweet potatoes, pumpkin, chestnuts, ginger, onions, scallions, flat mushrooms, cucumbers, string beans
Meat, poultry and eggs (6 kinds from 40 pages)	Pork, duck, beef, chicken, lamb, egg
Aquatic products (10 kinds from 40 pages)	Yellow croaker, salmon, scallop, cod, white shrimp, Arctic sweet shrimp, crab, oyster, scallop, sea cucumber
Pasta and cooked food (10 kinds from 32 pages)	Hand Pie, noodle with meat sauce, siu mai, xiao long bao, soup dumpling, dumpling, mousse, pie, chicken tenderloin, meat dumpling

Source: Jingdong

Following fresh product categorization (fruits, vegetables, meat, poultry and eggs, aquatic products, pasta, and cooked food), we targeted top-selling categories on the JD platform for review crawling. This yielded 61 product types across 185 stores. Details of the fresh food category selection are presented in Tab. 1.

In this paper, we have collected two datasets, dataset 1 is the core data which is used for regression analysis and needs prediction, dataset 2 is used for training. In this light, we employ Python for crawling review data of selected products, and parse JSON response to extract customer IP addresses, creation times, ratings, review texts, and other relevant fields. Ultimately, we obtain 148,787 pieces of data from March 2023 to May 2024 (dataset 1), after filtering and removing 34,612 redundant comments lacking IP information or duplicates. Preprocessing, including word segmentation and stopwords removal, yields a dataset with words as the fundamental unit. Additionally, we collect 157,068 reviews of similar fresh food e-commerce types from January 2020 to May 2024 (dataset 2) to train the Word2vec-SVM model. We open source the code and data at https://github.com/allen-zqh/code-data-for-EM-journal.

2.3 Extraction of service quality evaluation indicators based on LDA

When composing reviews, consumers often focus on specific themes relevant to their shopping experiences. These themes or topics, comprising characteristic and emotion-laden words, are key aspects reflected in reviews. This study utilizes LDA to cluster review themes, subsequently assigning manual labels to these clusters, which serve as evaluation indicators for fresh food e-commerce service quality. The process involves:

i) Data preprocessing: removing meaningless and short words to construct an effective bag-of-words (BoW) model for LDA modeling.

ii) Determining the number of topics: evaluating perplexity and coherence. Observing the relationship between model indicators and topic numbers (Fig. 1), a significant inflection point is noted at nine topics, indicating optimal model performance, thus, nine topics are selected.

iii) LDA modeling: utilizing the word frequency-inverse document frequency (TF-IDF) to extract text features, followed by fitting the LDA model with 5 passes, batch model and filtering words whose frequency is less

Tab. 2: Summary of service quality – Part 1

Indicators	LDA	Keywords	Explanations
Quality assurance	#1	Fresh, packaging, data, taste, flavor	1. Received products that are fresh, of good quality and taste 2. Delivered with complete and clean packaging and undamaged products 3. There are cold storage measures, such as cold chain transportation, equipped with a warm box, and ice bags
	#2	Ice, pack, frozen, tender, rich	
Reliability	#3	Worthwhile, quality, recommendation, trust, brand	1. The firm is professional, reputable and trustworthy 2. Be able to deliver the goods on time, fast delivery speed 3. The delivered goods are consistent with the order information 4. Delivery personnel dress neatly and hygienically, formal and unified
	#4	Packaging, reassuring, logistics, punctual	
Responsiveness	#5	Morning, soon, next day, today	1. Timely response to orders and prompt delivery 2. In-transit logistics information is updated promptly and accurately 3. Timely after-sales processing, fast return, replacement and compensation 4. Timely customer service response, fast feedback on inquiries and complaints
	#6	Logistics, express, speed, order, fast	

Tab. 2: Summary of service quality – Part 2

Indicators	LDA	Keywords	Explanations
Empathy	#7	Courier, attitude, believe, express, thanks, praise, recommend, sachet, service	1. Provide personalized service to customers, can take the initiative to understand and meet customer needs 2. Delivery personnel service warm and courteous, good attitude 3. Be able to patiently answer customers' questions when communicating with them 4. Promptly inform customers of any precautions 5. Be able to take the initiative to remind and contact customers when delivering goods
Economy	#8	Price, event, affordable, bargain, supermarket, double 11, full discount, price performance ratio	1. Freight costs are cost-effective 2. The return logistics cost is reasonable and supported by shipping insurance 3. There are special offers for reduced shipping costs
Convenience	#9	Convenient, door-to-door, deliver to my home, just right, direct, no need, efficient, easy, quick	1. Wide range of logistics services, high coverage of distribution network 2. Flexible collection time, customers can choose the collection time independently 3. Flexible pickup mode, customers can independently choose to deliver to their doorsteps or pick up at the post station 4. Convenient operation of payment, return and exchange processes

Source: own

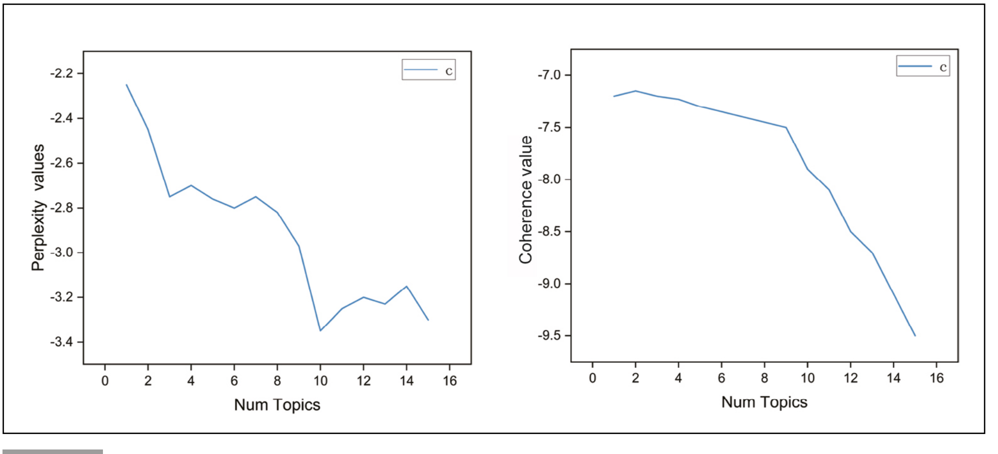

Fig. 1: Perplexity and coherence score and number of topics

Source: own

than 5. Upon model training completion, texts are assigned topics, and the probability distribution of each text belonging to each topic is computed as well.

Continuous adjustments to the stopword list and customized lexicon are made based on topic outputs from multiple experiments to minimize noise during clustering. Finally, six topics (indexes) are generalized by combining the classical scales such as SERVQUAL and LSQ, including quality assurance, reliability, responsiveness, empathy, economy, and convenience (Tab. 2).

2.4 Quantification of service quality in fresh food e-commerce

In constructing the emotional lexicon for analyzing online reviews, we delineate two predominant structures: "degree word + emotional feature word" and "degree word + negative word + emotional feature word." For instance, phrases like "not very fresh" exemplify these structures, with "very" serving as a degree word, "not" as a negative word, and "fresh" as an emotional feature word. Thus, the construction of the emotional lexicon entails the creation of dictionaries for emotional characteristics, negation words, and degree words.

i) Dictionary of emotional characteristics. We organize and optimize keywords obtained from LDA clustering and high-frequency words, aligning them with the six evaluation indicators of fresh food e-commerce service quality. This process yields a lexicon of logistic core words corresponding to each indicator.

ii) Dictionary of negation words. Drawing from existing Chinese negative word dictionaries available online, we identify and retain applicable negatives observed in fresh food e-commerce reviews. Irrelevant negatives are eliminated, resulting in the completion of the negation dictionary.

iii) Dictionary of degree words. Degree words modify or intensify the emotional intensity of an emotional word. We adapt an existing Chinese degree word dictionary, comprising 219 words categorized into six intensity levels. Additionally, we augment this dictionary with sentiment words extracted from high-frequency words in the sample data, relevant to fresh food e-commerce, such as "very good," "lightning speed," and "no complaints." These words are assigned values in the interval [0.5, 2], classified into six grades.

After constructing the sentiment lexicon, sentiment analysis is employed to quantify the sentiment value of each indicator's feature word in the reviews. The sentiment score of each sentiment feature word in a comment is calculated, and then the sentiment scores of the sentiment feature words belonging to each indicator are aggregated. This calculation is represented by Equation (1):

$$Sentiment = \sum_{i=1}^{n}\sum_{j=1}^{m} degree_j \times n_i \times negative^k \qquad (1)$$

where: *sentiment* – the sentiment score of a topic in the comment; n_i – the emotional characteristics with i = 1, 2, …, n; n – the number of emotional characteristics in the comment; $degree_j$ – the degree; j = 1, 2, ..., m, where m is the number of degree words neighboring the emotional characteristics; $negative^k$ – the negative word; k – number of negatives neighboring the emotional characteristics or degree word.

The constructed sentiment lexicon is employed to transform qualitative data into quantitative data, facilitating the calculation of scores for each review across the six indicators: quality assurance, reliability, responsiveness, empathy, economy, and convenience. A dataset comprising 125,027 valid entries was obtained.

2.5 Quantification of customer satisfaction

To enhance the accuracy of textual analysis, this study employs classification algorithms like logistic regression, random forest, and SVM for model training, assessing their performance using metrics such as precision, recall, and F1-score. Notably, the Word2vec-SVM model works better compared to conventional machine learning methods in previous studies (Yang et al., 2022). Hence, Word2vec is integrated with machine learning to encode evaluation sequences. By leveraging Word2vec-generated word vectors as input features for SVM classifiers, textual sentiment can be effectively classified and recognized. This approach combines the semantic information capture capability of Word2vec with the robust classification performance of SVM, enhancing the accuracy and efficiency of sentiment analysis.

Therefore, this paper utilizes Word2vec-SVM model to quantify customer satisfaction. Specifically, we used dataset 2 (157,068) for training.

Tab. 3: Satisfaction based on Word2vec-SVM

Origin comments	Consumer satisfaction	Overall statistics
The packaging was secure and well-sealed, and JD logistics delivered the package very quickly, arriving the next day. The cherries were large, tasted good, and were very fresh. Moreover, JD's pricing is quite reasonable, more competitive than supermarket prices. Highly recommended.	0.1000	Max: 1.0000 Min: 0.0000 Std: 0.3396 Mean: 0.8338
JD's self-operated delivery is incredibly fast. I placed the order last night, and it arrived early this morning. Some of the items were already dry, but they tasted great. I'll order again after finishing these. I've had my eye on this item for a while, and the promotion made it such a great deal. If you like it, don't hesitate!	0.9917	
I placed an order on November 25th, and it still hasn't shipped. This one, which I ordered a few days ago, shipped surprisingly fast. It came in a thermal box, and the quality is decent, though a few were spoiled. The taste is acceptable, slightly sour.	0.0784	
It feels like the items were ripened in cold storage; they don't taste particularly fresh.	0.0556	

Source: own

In order to avoid the tediousness of manual labeling, this paper collects reviews according to "good" (79,851) and "bad" (77,217), respectively. Secondly, after cutting words and removing stop words (like "is," "and," "to," "of"), Word2vec is used to vectorize the preprocessed text, where the word vector dimension is 500, the number of iterations is 10, and the low-frequency word threshold is 5. The model is trained using logistic regression, random forests, SVM, and Word2vec-SVM, respectively (Fig. 2). Finally, Word2vec-SVM with better results was selected to predict the 148,787 data (dataset 1) in this paper to obtain customer satisfaction scores (7:3 for selecting training and testing data, the kernel is "rbf," both verbose and probability are "true"). Tab. 3 shows some selected comments with predicted consumer satisfaction.

3. Empirical analysis

3.1 Variables

In this paper, the impact of the six evaluation indicators of fresh food e-commerce service quality on customer satisfaction is analyzed as a main effect in empirical analysis.

The explanatory variable is customer satisfaction, which is the probability of classification each text review as an input to the trained Word2vec + SVM model, in other words, the general level of satisfaction exhibited by each comment.

The core explanatory variables are the six indicators, which are quality assurance, reliability, responsiveness, empathy, economy, and convenience, and their specific interpretations are shown in Tab. 2, and the specific values are derived from the results of the sentiment value score. We trained and evaluated four different models for sentiment analysis: support vector machine (SVM), random forest, logistic regression, and a Word2Vec-based model. Each model has distinct characteristics. SVM is effective for high-dimensional text data classification and can handle non-linear decision boundaries. Random forest is robust to noise and helps prevent overfitting by averaging the results of multiple decision trees. Logistic regression is a linear model known for its simplicity and interpretability, often used for binary classification tasks like sentiment analysis. The Word2Vec-based model utilizes word embeddings to capture semantic relationships between words, making it particularly effective in understanding the context within text. We evaluated each model using precision, recall, and F1-score to select the best-performing one. Precision measures the accuracy of positive predictions, recall assesses the model's ability to identify all positive instances, and

F1-score provides a balanced metric of both precision and recall. The model with the highest F1-score was chosen as the final tool for sentiment analysis.

On the basis of the main effect, this study aims to delve deeper into how customer geographic location and purchase timing influence the primary effect's variation. Thus, customer location and purchase timing are transformed into interaction variables, which are then incorporated into the regression model for analysis. IP address information is utilized to derive two specific variables: logistical distance and regional economic status. Additionally, purchase timing information is converted into a seasonal variable.

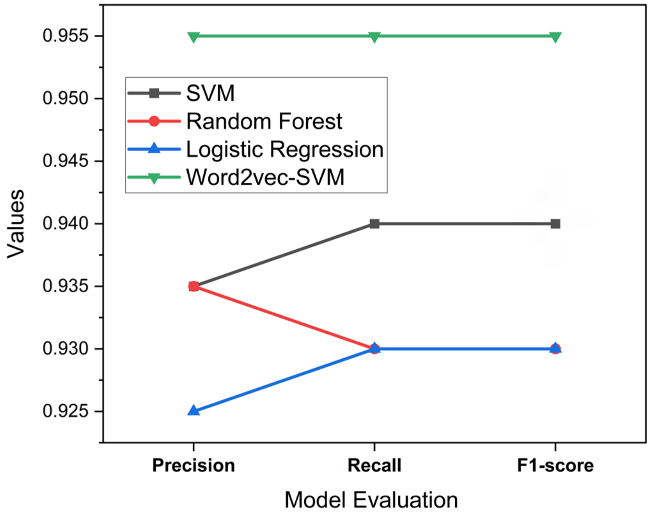

Fig. 2: Model evaluation summary

Note: The word vector dimension is 500; the number of iterations is 10; the threshold of low-frequency words is 5; dividing the training set and the test set in the ratio of 7:3.

Source: own

i) Logistics transportation distance. IP address for each review on the JD Fresh food platform is province-level. Consequently, the capital city in each province is considered the receiving location. Data collection encompasses 31 provinces in China, excluding Hong Kong, Macao, and Taiwan. The selected review data pertain to JD's own fresh goods, making cities housing JD's seven logistics centers the delivery locations.

Logistics distance herein refers to the spherical distance between the warehouses and receiving places. It operates under the assumption that JD opts for the warehouse closest to the receiving site for shipping. To facilitate computation, data is discretized using the natural breakpoint method, categorizing logistics transportation distances into seven categories. Larger values denote greater distances as shown in Fig. 3.

ii) Season. To elucidate the time variable, this study employs the four seasons, characterized by distinct temperature variations (seasons are delineated according to the northern hemisphere's Gregorian calendar, with spring spanning March, April, and May; summer covering June, July, and August; fall encompassing September, October, and November; and winter spanning December, January, and February). Typically, average temperatures follow the order: summer > spring = fall > winter. Thus, summer is assigned 3, spring and fall are assigned 2, and

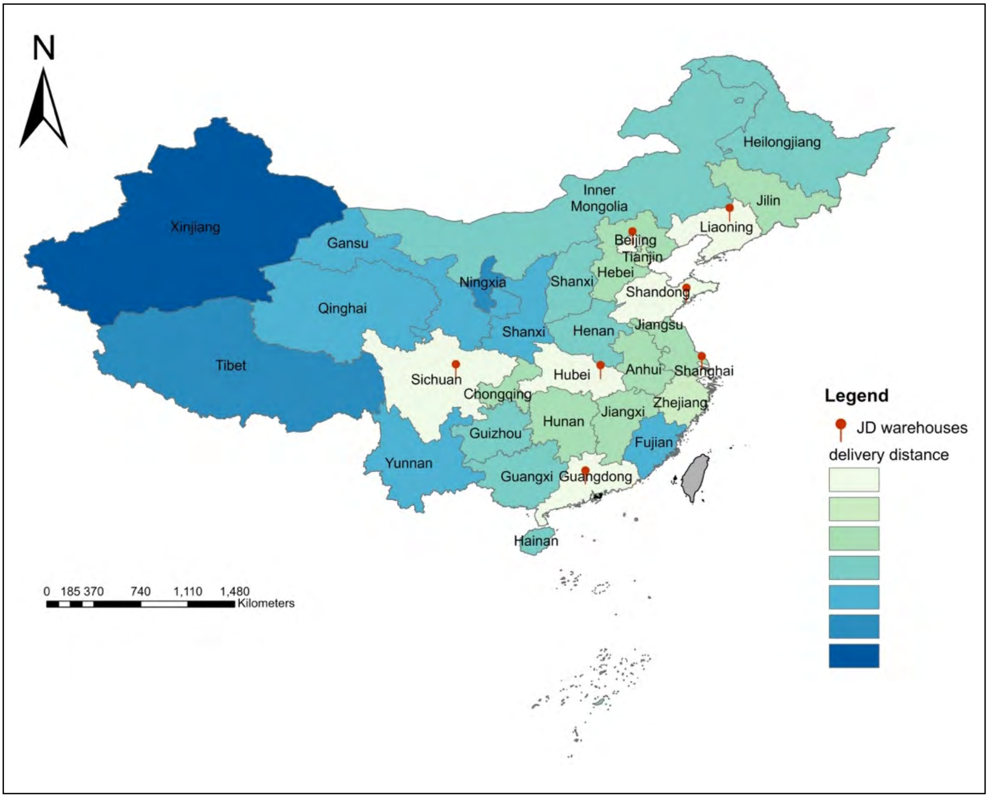

Fig. 3: Classification of logistics and transportation distances

Note: Hong Kong, Macao and Taiwan were not included due to lack of data.

Source: Jingdong and own

winter is assigned 1. Higher temperatures correspond to larger values in this scale.

iii) Regional economic level. This study employs GDP per capita data to depict the economic condition of consumers in each area, sourced from the China Statistical Yearbook 2023. Utilizing the natural breakpoint method, we categorized the economic status of each region into seven tiers. Larger values denote higher economic levels within the region. The descriptions of the variables are summarized in Tab. 4.

3.2 Regression model

In order to explore the influence of each indicator on customer satisfaction, we employ a multiple linear regression model for empirical analysis. The regression comprises main effect and interaction effect regression. The main effect examines the impact of each indicator of fresh e-commerce service quality on customer satisfaction. Conversely, the interaction effect scrutinizes how each indicator affects customer satisfaction under the perturbation of spatio-temporal factors, namely logistics transportation distance, economic level, and season.

1) Main effect model:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{p=1}^{k} \sigma_p z_p + \varepsilon \qquad (2)$$

2) Interaction effect model:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \alpha_j m_j + \\ + \gamma_j m_j \sum_{i=1}^{n} x_i + \sum_{p=1}^{k} \sigma_p z_p + \varepsilon \qquad (3)$$

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \alpha_j m_j + \\ + \gamma_j m_j \sum_{i=1}^{n} x_i + \sum_{p=1}^{k} \sigma_p z_p + \lambda + \varepsilon \qquad (4)$$

Tab. 4: Summarization of variables and descriptions

Variable type		Symbol	Definition	Description
Control		C1	Price	Price per unit of fresh goods
		C2	Cumulative comments	Number of reviews for fresh products
		C3	Purchase frequency	Purchase times for each user
Independent	Core explanatory variables	X1	Quality assurance	Value obtained from the sentiment dictionary calculation
		X2	Reliability	
		X3	Responsiveness	
		X4	Empathy	
		X5	Economy	
		X6	Convenience	
	Interaction variables	M1	Logistics transportation distance	Distance from JD's own warehouse to the place of delivery
		M2	Regional economic level	GDP per capita in 2023 for all provinces and cities in the country
		M3	Season	3-classes according to temperature
Dependent		Y	Consumer satisfaction	Predicted value of Word2vec-SVM

Source: own

where: Y – customer satisfaction; β_0, β_1, β_2, .., σ_p – regression coefficients; n = 6; k = 2; x_i – the scores of each indicator of service quality of fresh e-commerce; i = 1, 2, …, 6; m_j – the interaction variables, i.e., the values of logistics and transportation distances, economic levels, and seasons; j = 1, 2, …, 6; z_p – control variables, i.e., the price of the product and the number of review entries; λ – the fixed effect of product type; ε denotes random error and $\varepsilon \sim N(1, \sigma^2)$.

3.3 Results

From the main effect regression results in Tab. 5, it is evident that enhancing quality assurance, reliability, responsiveness, empathy, economy, and convenience in logistics services is conducive to improving service quality. The degree of influence, ranked in descending order based on the size of coefficients, is as follows: quality assurance > economy > convenience > reliability > responsiveness > empathy. Quality assurance exerts the most substantial impact on service quality due to its direct correlation with product quality, especially considering the perishable nature of fresh products. The economy, holds the second-highest impact, indicating consumers' sensitivity to pricing, which significantly influences their shopping decisions and experiences. Convenience, reliability and responsiveness also have a positive impact on the evaluation of service quality, indicating that flexible pickup, safe and fast delivery of goods, the compatibility of goods and descriptions, the speed of shipment and the speed of customer service feedback, etc., are also the focus of customers. In contrast, the impact of empathy on service quality evaluation is relatively lower, suggesting that consumers may allocate less attention to factors like staff service attitude during the evaluation process.

The regression results for the interaction effects are shown in Tab. 6. We interpret them

Tab. 5: Main effect regression results

	Model 1	Model 2
Price	0.000***	0.000***
	(0.000)	(0.000)
Cumulative comments	−0.000***	−0.000***
	(0.000)	(0.000)
Quality assurance		0.068***
		(0.000)
Reliability		0.032***
		(0.001)
Responsiveness		0.030***
		(0.001)
Empathy		0.013***
		(0.001)
Economy		0.058***
		(0.001)
Convenience		0.072***
		(0.001)
_cons	0.773***	0.599***
	(0.002)	(0.002)
Type	Yes	Yes
Month	Yes	Yes
N	124,608	124,608
***R*²**	0.015	0.310

Note: Robust standard errors calculated in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: own

in the following three aspects: interaction effect with logistics transportation distance; interaction effect with regional economic level; interaction effect with season.

Interaction effect with logistics transportation distance

Firstly, the interaction effect between logistics transportation distance and quality assurance is found to be negative and significant. This suggests that as the distance increases, consumers may expect a wider range of acceptable quality due to longer transportation times.

Similarly, the interaction effect between logistics transportation distance and economy also shows a negative significance, indicating that longer transportation distances diminish the influence of economy on customer satisfaction. Higher postage charges for distant regions, as practiced by JD self-supporting, may contribute to this trend. For example, in many free shipping products, it is stated that Xinjiang, Tibet and other remote areas are excluded. This practice makes consumers from remote areas accustomed to the cost of postage, resulting in a reduction of their economic sensitivity.

Moreover, the interaction effect between logistics transportation distance and responsiveness is negatively significant, that longer transportation distances tend to reduce the impact of responsiveness on customer satisfaction. The inherently longer transportation time in remote areas diminishes the marginal benefit of delivery speed, reducing consumer attention to responsiveness. In addition, by going back to the product details page, we found that when the transportation distance is farther away from the region, JD generally do not provide perishable fresh food delivery service. Therefore, consumers in these areas are more able to purchase fresh products that are relatively less susceptible to damage and spoilage, such as instant food products with packaging and relatively long shelf life, as well as fruits and vegetables with hard skin, which also reduces consumer demand for timely delivery.

Interestingly, the interaction effect between logistics transportation distance and

Tab. 6: Regression results of interaction effects – Part 1

	Model 3	Model 4	Model 5
Price	0.000***	0.000***	0.000***
Cumulative comments	(0.000)	(0.000)	(0.000)
Quality assurance	−0.000***	−0.000***	−0.000***
Reliability	(0.000)	(0.000)	(0.000)
Responsiveness	0.068***	0.068***	0.046***
Empathy	(0.000)	(0.000)	(0.001)
Economy	0.032***	0.032***	0.022***
Convenience	(0.001)	(0.001)	(0.002)
Logistics transportation distance	0.030***	0.030***	0.024***
Quality assurance – distance	(0.001)	(0.001)	(0.002)
Reliability – distance	0.013***	0.013***	0.007***
Responsiveness – distance	(0.001)	(0.001)	(0.002)
Empathy – distance	0.058***	0.058***	0.044***
Economy – distance	(0.001)	(0.001)	(0.002)
Convenience – distance	0.072***	0.072***	0.072***
Regional economic level	(0.001)	(0.001)	(0.001)
Quality assurance – economy	−0.000***		
Reliability – economy	(0.000)		
Responsiveness – economy	−0.000***		
Empathy – economy	(0.000)		
Economy – economy	0.000		
Convenience – economy	(0.000)		
Season	−0.000**		
Quality assurance – season	(0.000)		
Reliability – season	0.000		
Responsiveness – season	(0.000)		
Empathy – season	−0.000*		
Economy – season	(0.000)		

Tab. 6: Regression results of interaction effects – Part 2

	Model 3	Model 4	Model 5
Convenience – season Price	0.000*		
	(0.000)		
Cumulative comments Quality assurance		0.000***	
		(0.000)	
Reliability Responsiveness		−0.000	
		(0.000)	
Empathy Economy		−0.000	
		(0.000)	
Convenience Logistics transportation distance		0.000	
		(0.000)	
Quality assurance – distance Reliability – distance		0.000	
		(0.000)	
Responsiveness – distance Empathy – distance		−0.000**	
		(0.000)	
Economy – distance Convenience – distance		−0.000***	−0.000***
		(0.000)	(0.000)
Regional economic level Quality assurance – economy			−0.034***
			(0.001)
Reliability – economy Responsiveness – economy			0.013***
			(0.001)
Empathy – economy Economy – economy			0.006***
			(0.001)
Convenience – economy Season			0.003***
			(0.001)
Quality assurance – season Reliability – season			0.004***
			(0.001)
Responsiveness – season			0.008***
			(0.001)
_cons	0.600***	0.599***	0.711***
	(0.002)	(0.002)	(0.004)
Type	Yes	Yes	Yes
Month	Yes	Yes	Yes
N	124,608	124,608	124,608
R^2	0.310	0.311	0.319

Note: Robust standard errors calculated in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: own

convenience is significantly positive, indicating that longer transportation distances increase the impact of convenience on customer satisfaction. Underdeveloped logistics infrastructure in remote areas may lead to difficulties in the "last kilometer" transportation and service guarantee, prompting consumers to prioritize flexible and convenient pickup options.

However, the regression coefficients of the interaction terms between transportation distance and reliability and empathy are not significant, indicating that transportation distance does not significantly influence consumer attention to these attributes.

Interaction effect with regional economic level

The regression analysis reveals intriguing insights regarding the relationship between the economic level of a region and various aspects of customer satisfaction in fresh food e-commerce. Specifically, the negative regression coefficient between economic level and economy suggests that in economically developed regions, affordability has a greater impact on customer satisfaction. This phenomenon stems from the higher purchasing power and reduced-price sensitivity of consumers in such areas compared to those in less developed regions.

However, the negative regression coefficients of both interaction terms of economic level with quality assurance and convenience are noteworthy. They imply that in economically developed regions, the influence of quality assurance and convenience on customer satisfaction diminishes. This trend may be attributed to the higher logistics standards and more comprehensive infrastructure in economically advanced areas, resulting in shorter transportation times and higher product freshness. Moreover, consumers in these regions may be accustomed to receiving quality goods and utilizing convenient pickup methods, thus these factors have less impact on their overall evaluation of fresh food e-commerce services.

Conversely, the positive regression coefficient of the interaction term between regional economic level and empathy indicates that in more economically developed regions, the impact of empathy on customer satisfaction is heightened. Consumers in these areas often have higher expectations regarding the service attitude and quality of delivery and customer service personnel. Based on a selection of representative comments (e.g., *Now frozen deliveries are either called or delivered to your door, but they just put it on the doorstep and walk away – Shanghai; The delivery guy comes to the door at 1:00 p.m., the kids are asleep, and he's rude enough to keep ringing the doorbell, can't he be a little quieter? – Beijing*), it is evident that consumers in economically developed regions have specific expectations regarding logistics service empathy.

However, the negative regression coefficient of the interaction term between regional economic level and reliability suggests that the influence of reliability on customer satisfaction may decrease in economically developed regions. This could be attributed to the prevalence of reliable logistics and distribution systems, resulting in the safe and timely arrival of goods becoming commonplace, thus receiving less attention in consumer reviews.

Interaction effect with season

The regression analysis in Tab. 5 reveals significant positive coefficients for the interaction terms between season and various service quality dimensions, including quality assurance, reliability, economy, empathy, and convenience.

Specifically, the positive regression coefficients of the interaction terms of season with quality assurance, as well as reliability, suggest that the hotter the season, the greater the effect of these attributes on customer satisfaction. This is due to the fact that in summer, when the weather is hot, fresh food is prone to corruption and deterioration, and the work of preservation is more difficult, and there will be higher requirements for the management of cold chain logistics, temperature control during transportation and storage, and speed of delivery, so that problems occurring in the logistic process are also more likely to be detected by consumers, and the consumers' evaluations of the warranty and reliability are more prone to fluctuate accordingly.

Unexpectedly, the regression coefficients of the interaction term between season and empathy and convenience are also significantly positive, indicating that the hotter the season, the greater the impact on customer satisfaction. As tracing the original comments reveals that when the weather is hot, consumers will have more obvious empathy for the delivery personnel, be more sympathetic to their labor, and be more appreciative of home delivery and other actions that can increase convenience, and will mention it more in their comments to express their gratitude, thus increasing the impact of convenience and empathy on satisfaction (e.g., *Mushroom package has been received, thanks to the Jingdong delivery, the box is intact, there is an ice pack. The courier has a good attitude of service, though summer is hot, you have worked hard*).

Similarly, economy, which should be independent of the season, shows a positive and significant relationship here, suggesting that the effect of economy on customer satisfaction increases in hotter seasons. By tracing the comments in the summer, we found that a large number of comments mentioned the words "event," "discount" and "subsidies," suggesting that this result may be related to JD's "618" campaign. Although there is multiple "shopping festivals" in a year, because "618" originates from JD, JD's preferential and promotional efforts will be greater than other shopping festivals, and consumers are more likely to associate "618" with JD. As a result, the organization of large-scale promotional activities will attract more economically sensitive consumers, leading to a significant increase in consumers' attention to economy.

Although the coefficient for the interaction term of season with responsiveness is only positively significant at the 10% level, it still suggests that the season will increase the effect of responsiveness on customer satisfaction to some extent. The reason for this may be due to the temperature will have a certain impact on human emotions, research has shown that summer is prone to "emotional heat stroke" phenomenon, people are relatively easy to produce impatient emotions, which may also lead to the increase in the responsiveness of the logistics service requirements.

3.4 Heterogeneity analysis based on consumer type of first-time and repeated

In addition to the core logistics service quality and spatiotemporal factors influencing customer satisfaction, consumers' purchasing experiences also shape their expectations and perceptions of service. For instance, first-time buyers may have different expectations compared to repeat purchasers. To validate the robustness of our findings across other platforms and account for purchase frequency, we collected 278,705 JD Jingzao reviews – JD Jingzao being JD's curated shopping platform, which operates differently from JD's main platform. Unlike dataset 1, which includes both self-operated and third-party businesses, JD Jingzao is fully self-operated under a distinct brand. This dataset includes consumer purchase frequency data, centralizing it alongside the five logistics service quality factors for further regression analysis. The results are presented in Tab. 7.

Tab. 7: Heterogeneity analysis – Part 1

	Model 6	Model 7
Price	0.011***	0.011***
	(0.001)	(0.001)
Comments	−0.020***	−0.020***
	(0.001)	(0.001)
Quality assurance	0.044***	0.044***
	(0.001)	(0.001)
Reliability	0.052***	0.052***
	(0.001)	(0.001)
Responsiveness	0.038***	0.038***
	(0.001)	(0.001)

Tab. 7: **Heterogeneity analysis – Part 2**

	Model 6	Model 7
Empathy	0.015***	0.015***
	(0.001)	(0.001)
Economy	0.056***	0.056***
	(0.001)	(0.001)
Convenience	0.042***	0.043***
	(0.001)	(0.001)
Quality assurance – purchase		−0.000
		(0.000)
Reliability – purchase		−0.000
		(0.001)
Responsiveness – purchase		−0.002***
		(0.001)
Empathy – purchase		−0.002***
		(0.001)
Convenience – purchase		−0.005***
		(0.001)
_cons	0.709***	0.709***
	(0.001)	(0.001)
Type	Yes	Yes
N	278,705	278,705
R^2	0.222	0.222

Note: Robust standard errors calculated in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: own

As shown in Tab. 7, the impact of the five logistics service quality factors on satisfaction remains consistent with previous findings, affirming the robustness of our results. Additionally, the key interaction terms – responsiveness, empathy, and convenience – are significantly negative at the 1% level. This suggests that the marginal utility of logistics service quality decreases as consumers' purchase experience increases, highlighting that repeat customers tend to have more stable and demanding service expectations compared to new customers. Furthermore, drawing on the two-factor theory in e-commerce and customer satisfaction (Alshmemri et al., 2017), these significantly negative factors align more with "attraction" attributes, as opposed to basic factors like assurance and reliability, particularly in the context of fresh goods. These attributes play a greater role in enhancing customer satisfaction and overcoming perception bottlenecks (Yang & Huang, 2024). This finding also indicates that experienced consumers prioritize further improvements in service quality.

Conclusions and discussion

This paper investigates the impact of fresh food e-commerce service quality on customer satisfaction using online reviews from JD Fresh. Firstly, based on LDA model, topic clustering was carried out on online reviews, six evaluation indicators of fresh food e-commerce service quality were identified, and each indicator was scored by using sentiment analysis; secondly, the customer satisfaction of the reviews was measured by machine learning. Based on the measurement results, we explored the impact of fresh e-commerce service quality on customer satisfaction; innovatively, we introduced spatial and temporal factors, including logistics transportation distance, regional economic level, and season, as interaction variables. Through regression analysis, we examined the influence of service quality indicators on customer satisfaction, along with the perturbation effects of temporal and spatial factors.

Our findings highlight that: i) Based on users' online reviews, the evaluation indicators of fresh food e-commerce service quality can be summarized as quality assurance, reliability, responsiveness, empathy, economy, and convenience. ii) From the results of the main effects, quality assurance, reliability, responsiveness, empathy, economy, and convenience all have a positive and significant impact on customer satisfaction, and quality assurance > economy > convenience > reliability > responsiveness > empathy, indicating that quality assurance has the greatest impact on customer satisfaction and is most valued by consumers, which is similar to previous results of service quality in Parasuraman et al.'s (1998) research. But the result of importance is opposite to Yang et al.'s (2024) study for emotional service can better improve consumer satisfaction, which suggests that there are boundaries that influence consumer satisfaction, such as temporal-spatial factors and consumer purchases mentioned later. iii) From the results of interaction effect, the further the logistics transportation distance is, the impact of quality assurance, economy and responsiveness on customer satisfaction will be weakened, and the impact of convenience on customer satisfaction will be strengthened, which is the same effect of distance on consumer textual emotion (Neumann et al., 2023). The higher the economic level is, the impact of economy, quality assurance, convenience and reliability on customer satisfaction will be reduced, and empathy has an increased effect on customer satisfaction, which is also aligns with the impact of economic value perception on consumer decisions (Istanti et al., 2020). The higher the temperature season, the effect of all six attributes on customer satisfaction is significantly increased. iv) For the heterogeneity analysis of consumer purchase times, compared with first-time users, repeated customers with more purchases have higher requirements for logistics services, especially focused on charm factors, it corresponds to the asymmetric relationship between consumers with different visit frequencies (Schofield et al., 2020).

Our empirical results shed light on improving the logistics services of fresh food e-commerce. For example, firms should prioritize the improvement of quality assurance over the improvement of service quality. The results of the interaction effects provide some more specific strategic directions: from the perspective of transportation distance, fresh food e-commerce companies should enhance local customer service support in areas with shorter transportation distance to respond to consumer demand faster; while for remote areas, they need to improve the construction of logistics support facilities. From the perspective of the level of regional development, firms need to strengthen the level of personalized service to consumers in economically developed regions; more targeted preferential events for consumers in less economically developed regions. From the seasonal point of view, firms need to strengthen the control of quality assurance in the hot season; and appropriately increase the number of employees and employee care, in order to help incentivize the delivery staff to improve the level of service, so as to enhance the overall evaluation of the quality of service to consumers. Moreover, firms can differentiate their services according to the type of consumers (first-time or repeated). They can use attract strategy for first-time consumers and retaining method for repeated consumers (Yang et al., 2024). Finally, large platforms like JD and Alibaba should leverage AI and big data technologies to optimize regional logistics and enhance cold chain capabilities, ensuring freshness and quality across all regions. Meanwhile, small to medium-sized companies, which often rely on third-party logistics, should focus on building flexible delivery networks and maintaining strong communication with customers to enhance satisfaction.

Additionally, this model can be adapted for use on other e-commerce platforms such as Alibaba and Amazon, which may have different logistics frameworks and customer expectations. For instance, in third-party logistics models commonly used by Amazon, reliability and responsiveness might play a more crucial role compared to JD's self-operated logistics.

Similarly, in international markets, cultural and regional differences could influence which aspects of logistics are most valued by customers. Adapting this model to different regions could involve reweighting specific logistics attributes to better reflect local preferences. Moreover, the model could be extended to different markets and logistics models. In regions where cold chain logistics are less developed, factors like reliability and timeliness may dominate customer satisfaction, while in developed markets, the focus may shift to convenience and responsiveness. Exploring how this model performs in these diverse environments can provide a more comprehensive understanding of the logistics satisfaction dynamics in fresh food e-commerce.

This study has limitations that we wish the future study to address. First of all, although we provided data for the hybrid operating model, the logistics scene for fresh food e-commerce is relatively narrow. Because different fresh food e-commerce companies in different countries have unavoidable differences, such as Taobao, Jingdong, Tiktok. Besides, since the secondary data from e-commerce platforms, we are unable to capture socio-demographic characteristics of consumers such as age and gender. Future research can consider a more detailed categorization of the logistics model of fresh food e-commerce and comparative analysis to make the results more precise in other regions outside of China. Follow-up studies can also incorporate questionnaires to compensate for demographic attributes as the mixed method. Finally, the accuracy of text analysis needs to be improved. Future research could build on this work by applying more advanced sentiment analysis techniques, such as deep learning models and aspect-based sentiment analysis (ABSA). Deep learning models, such as BERT and Transformer, can capture nuanced emotional expressions and improve sentiment classification accuracy. Meanwhile, ABSA would allow a more detailed examination of specific logistics service dimensions (e.g., delivery speed, product quality), offering a more granular understanding of their influence on customer satisfaction (Hajek et al., 2023; Huang et al., 2023).

References

Alshmemri, M., Shahwan-Akl, L., & Maude, P. (2017). Herzberg's two-factor theory. *Life Science Journal*, *14*(5), 12–16. https://doi.org/10.7537/marslsj140517.03

Anderson, E. W., Fornell, C., & Lehmann, D. R. (1994). Customer satisfaction, market share, and profitability: Findings from Sweden. *Journal of Marketing*, *58*(3), 53–66. https://doi.org/10.1177/002224299405800304

Beckers, J., Weekx, S., Beutels, P., & Verhetsel, A. (2021). COVID-19 and retail: The catalyst for e-commerce in Belgium? *Journal of Retailing and Consumer Services*, *62*, 102645. https://doi.org/10.1016/j.jretconser.2021.102645

Calheiros, A. C., Moro, S., & Rita, P. (2017). Sentiment classification of consumer-generated online reviews using topic modeling. *Journal of Hospitality Marketing & Management*, *26*(7), 675–693. https://doi.org/10.1080/19368623.2017.1310075

Feng, K., Yang, Q., Chang, X., & Y, L. (2021). Customer satisfaction evaluation method for fresh e-commerce based on online reviewsand stochastic dominance rules. *Chinese Journal of Management Science*, *29*(2), 205–216. https://doi.org/10.16381/j.cnki.issn1003-207x.2019.2108

Gao, H. (2021). Research on logistics risks of fresh e-commerce products from the perspective of supply chain management. In *Proceedings of 2021 2nd International Conference on Urban Engineering and Management Science (ICUEMS)* (pp. 40–43). IEEE. https://doi.org/10.1109/icuems52408.2021.00016

Hajek, P., Hikkerova, L., & Sahut, J.-M. (2023). Fake review detection in e-commerce platforms using aspect-based sentiment analysis. *Journal of Business Research*, *167*, 114143. https://doi.org/10.1016/j.jbusres.2023.114143

Haley, G. T. (2002). E-commerce in China: Changing business as we know it. *Industrial Marketing Management*, *31*(2), 119–124. https://doi.org/10.1016/s0019-8501(01)00183-3

Han, B. R., Sun, T., Chu, L. Y., & Wu, L. (2022). COVID-19 and e-commerce operations: Evidence from Alibaba. *Manufacturing & Service Operations Management*, *24*(3), 1388–1405. https://doi.org/10.1287/msom.2021.1075

He, B., Gan, X., & Yuan, K. (2019). Entry of online presale of fresh produce: A competitive analysis. *European Journal of Operational Research*, *272*(1), 339–351. https://doi.org/10.1016/j.ejor.2018.06.006

Huang, H., Zavareh, A. A., & Mustafa, M. B. (2023). Sentiment analysis in e-commerce platforms: A review of current techniques and future directions. *IEEE Access*, *11*, 90367–90382. https://doi.org/10.1109/access.2023.3307308

IIstanti, E., Sanusi, R., & Daengs, G. S. (2020). Impacts of price, promotion and go food consumer satisfaction in faculty of economic and business students of Bhayangkara University Surabaya. *Ekspektra: Jurnal Bisnis Dan Manajemen*, *4*(2), 104–120. https://doi.org/10.25139/ekt.v4i2.3134

Ji, C., Dong, X., & Lin, W. (2024). The effects of e-commerce adoption on the financial performance of agri-food enterprises in China. *Electronic Commerce Research*. https://doi.org/10.1007/s10660-024-09810-z

Limbourg, S., Giang, H. T. Q., & Cools, M. (2016). Logistics service quality: The case of Da Nang City. *Procedia Engineering*, *142*, 124–130.https://doi.org/10.1016/j.proeng.2016.02.022

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. https://doi.org/10.1016/j.elerap.2021.101103

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. https://doi.org/10.1016/j.aei.2023.101936

Ma, K. X., Mather, D. W., Ott, D. L., Fang, E., Bremer, P., & Mirosa, M. (2021). 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.https://doi.org/10.1108/ijrdm-04-2021-0184

Mentzer, J. T., Flint, D. J., & Kent, J. L. (1999). Developing a logistics service quality scale. *Journal of Business Logistics*, *20*(1), 9–32.

Mortimer, G., Andrade, M. L. O., & Fazal-e-Hasan, S. M. (2024). From traditional to transformed: Examining the pre- and post-COVID consumers' shopping mall experiences. *Journal of Retailing and Consumer Services*, *76*, 103583. https://doi.org/10.1016/j.jretconser.2023.103583

Neumann, J., Gutt, D., & Kundisch, D. (2023). Reviewing from a distance: Uncovering asymmetric moderations of spatial and temporal distance between sentiment negativity and rating. *MIS Quarterly*, *47*(4), 1709–1726. https://doi.org/10.25300/misq/2022/17037

Palese, B., & Usai, A. (2018). The relative importance of service quality dimensions in e-commerce experiences. *International Journal of Information Management*, *40*, 132–140. https://doi.org/10.1016/j.ijinfomgt.2018.02.001

Qian, L., & Chen, R. (2023). "Where you live determines how you are treated": E-commerce geography and digital inequality in China. *Eurasian Geography and Economics*, *66*(1), 97–122. https://doi.org/10.1080/15387216.2023.2210596

Schofield, P., Coromina, L., Camprubi, R., & Kim, S. (2020). An analysis of first-time and repeat-visitor destination images through the prism of the three-factor theory of consumer satisfaction. *Journal of Destination Marketing & Management*, *17*, 100463. https://doi.org/10.1016/j.jdmm.2020.100463

Shi, J., & Li, J. (2019). Comparative analysis of corporate social responsibility research at home and abroad based on CiteSpace. *Journal of Beijing Institute of Technology (Social Sciences)*, *1*, 65–73 (in Chinese). https://doi.org/10.15918/j.jbitss1009-3370.2019.1912

Song, Z., & He, S. (2018). Contract coordination of new fresh produce three-layer supply chain. *Industrial Management & Data Systems*, *119*(1), 148–169. https://doi.org/10.1108/imds-12-2017-0559

Steinker, S., Hoberg, K., & Thonemann, U. W. (2017). The value of weather information for e-commerce operations. *Production and Operations Management*, *26*(10), 1854–1874. https://doi.org/10.1111/poms.12721

Tontini, G., Söilen, K. S., & Zanchett, R. (2017). Nonlinear antecedents of customer satisfaction and loyalty in third-party logistics services (3PL). *Asia Pacific Journal of Marketing and Logistics*, *29*(5), 1116–1135. https://doi.org/10.1108/apjml-09-2016-0173

Tsang, Y. P., Wu, C. H., Lam, H. Y., Choy, K. L., & Ho, G. T. S. (2021). Integrating internet of things and multi-temperature delivery planning for perishable food e-commerce logistics: A model and application. *International Journal of Production Research*, *59*(5), 1534–1556. https://doi.org/10.1080/00207543.2020.1841315

Wang, H., Li, W., Li, M., Yang, X., Wang, Z., Zhao, Z., & Wang, L. (2022). Intelligent selection of delivery parties for fresh agricultural product based on third-party logistics in smart city. *Sustainable Energy Technologies and As-*

sessments, *52*, 102151. https://doi.org/10.1016/j.seta.2022.102151

Wang, J., Zhao, Z., Liu, Y., & Guo, Y. (2021). Research on the role of influencing factors on hotel customer satisfaction based on BP neural network and text mining. *Information*, *12*(3), 99. https://doi.org/10.3390/info12030099

Yang, L., & Tang, R. (2019). Comparisons of sales modes for a fresh product supply chain with freshness-keeping effort. *Transportation Research Part E: Logistics and Transportation Review*, *125*, 425–448. https://doi.org/10.1016/j.tre.2019.03.020

Yang, Y., & Huang, J. (2024). Speaking with a "forked tongue" – Misalignment between user ratings and textual emotions in LLMs. *Kybernetes*. https://doi.org/10.1108/k-06-2024-1458

Yang, Y., Huang, J., Wu, G., Ma, Y., & Guo, Q. (2024). Applying kansei engineering and text mining to design fresh food logistics services. *International Journal of Logistics Research and Applications*, 1–25. https://doi.org/10.1080/13675567.2024.2316640

Yang, Y., Ma, Y., Wu, G., Guo, Q., & Xu, H. (2022). The insights, "comfort" effect and bottleneck breakthrough of "e-commerce temperature" during the COVID-19 pandemic. *Journal of Theoretical and Applied Electronic Commerce Research*, *17*(4), 1493–1511. https://doi.org/10.3390/jtaer17040075

Zahran, S. (2024). Optimizing supply chain management of fresh e-commerce agri-consumer products using energy-efficient vehicle routing. *IEEE Transactions on Consumer Electronics*, *70*(1), 1685–1693. https://doi.org/10.1109/tce.2024.3370845

Zhang, S., & Hou, Y. (2013). Measuring service quality of supply chain with SERVQUAL. *Information Technology Journal*, *12*(16), 3785. https://doi.org/10.3923/itj.2013.3785.3787

Zhao, X., Zhao, K., & Deng, J. (2019). Geography still matters: Examine the role of location in online markets for foreign branded products. *Decision Sciences*, *50*(2), 285–310. https://doi.org/10.1111/deci.12337