

Article

Understanding Customer Opinion Change on Fresh Food E-Commerce Products and Services—Comparative Analysis before and during COVID-19 Pandemic

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Abstract: During the coronavirus disease 2019 (COVID-19) pandemic, non-face-to-face e-commerce has become a significant consumer channel for customers to buy fresh food. However, little is known about customer opinion changes in fresh food e-commerce (FFEC) products and services during COVID-19. This study investigated the changes in expectations and preferences of FFEC customers on products and services before and during the pandemic from online reviews through a text mining approach. We divided the pandemic into two phases, acute and recovery, and found that eight attributes affect customers' opinions. Some logistic service-related attributes gained customer attention during the acute phase, but product-related attributes gained more attention in the recovery phase. Customers showed a great level of forgiveness on many attributes during the acute phase, but customers' dissatisfaction was expressed during the recovery phase. Finally, the results of the comparative importance–performance analysis provide improvement strategies for FFEC and help optimize their resource allocation of FFEC and enhance sustainable operation capacity in the case of a crisis.

Keywords: online review; customer satisfaction; sentiment analysis; CIPA; COVID-19; fresh food e-commerce



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1. Introduction

The outbreak of coronavirus disease 2019 (COVID-19) has had an impact on many areas. Many countries have taken measures, such as restricting entry, social distancing, and staying at home, to slow the diffusion of COVID-19 worldwide [1]. Moreover, many industries have been badly affected, such as the hospitality business and logistics industry [2]. However, social distancing and customer concerns about health and safety have contributed to the rapid growth of e-commerce [3]. Non-face-to-face online consumption has become a significant consumption channel. During the pandemic, online consumption of fresh food has increased, and fresh food e-commerce has become more active. Every additional confirmed patient of COVID-19 increased transactions of fresh food e-commerce by 5.7% and the number of customers by 4.9% [4]. Taking Shanghai as an example, in the first quarter of 2020, when the COVID-19 epidemic was severe, fresh food e-commerce saw sales increase by 167% year-on-year, and orders increased by 80% (<https://www.sh.gov.cn/swdt/20200414/1137467adefb4ef6bd896d7f774884e8.html> (accessed on 13 April 2020)).

In addition to increasing customers' willingness to buy fresh food from e-commerce channels, the COVID-19 outbreak has also affected customers' expectations and preferences [5]. Fresh food e-commerce faces tremendous pressures to meet the evolving customer

needs, which may influence customer satisfaction and finally make or break their business. Previous literature on the impact of COVID-19 on fresh food e-commerce studied the change in food prices during the pandemic situation [6], customer demand, and customer consumption frequency for online fresh food during the pandemic [4,7,8], the change in fresh food distribution and retail models owing to the COVID-19 outbreak [9,10], factors influencing the purchasing tendency of fresh food e-commerce customers [11–15], and factors affecting customer satisfaction during the pandemic [8,16,17].

In summary, the existing literature has conducted extensive research on the impact of COVID-19 on fresh food e-commerce. However, there are still gaps that need to be addressed. Few studies focused on the changes in customers' opinions through comparative analysis of customers' expectations and satisfaction before and during the pandemic, which is a crucial way to meet customer needs and improve customer satisfaction during a crisis. Existing studies often focus on the fresh food e-commerce sector during the pandemic, lacking comparative research and in-depth analyses on changes in consumer opinions at the product and service attribute levels. Therefore, the present study aims to reveal customers' opinions change on fresh food e-commerce products and services before and during the pandemic to help fresh food e-commerce improve their customer satisfaction in the case of a crisis.

With the expansion of online shopping, online reviews, as a form of user-generated content posted by customers spontaneously, have become a significant source of data for assessing customer satisfaction [18]. Online reviews help not only potential customers make purchase decisions [19], but also managers identify factors affecting satisfaction [20–22] and improving products or services [23–26]. In summary, online reviews are an effective way to understand customers. Therefore, online reviews are used in the present study to reveal changes in customers' opinions. To this end, the following questions will be answered in this study:

- (1) What are the attributes of fresh food e-commerce products and services that affect customers' opinions?
- (2) How can text mining of online reviews determine that the importance of attributes customers attach to fresh food e-commerce products and services have changed during the COVID-19 pandemic?
- (3) Through attribute-level sentiment analysis, how did customers' opinions change on the product–service performance of fresh food e-commerce during the COVID-19 pandemic?
- (4) From the changes in the importance and customer satisfaction of product–service attributes, what enlightenment can be drawn from fresh food e-commerce to cope with the sudden pandemic?

This study makes three major contributions. First, utilizing online review-mining techniques and conducting comparative analysis before and during the pandemic, this study identified the varying customer attention and evaluation of product service attributes of fresh food e-commerce. It is based on online reviews and explores customer opinion changes at the attribute level across the different stages of COVID-19, enriching and expanding current research on e-commerce during COVID-19. Second, through the comparative importance–performance analysis (CIPA) model, this study offers strategies that fresh food e-commerce businesses can adopt in response to sudden pandemics to enhance operations and increase satisfaction. Third, the integrated text-mining methodology employed in this study can provide insights for analyzing customer opinion changes in other fields as well.

This study is further structured as follows. Section 2 shows the literature review, and Section 3 introduces the methodology, which contains data collection and preparation and specific research methods used in this study. Section 4 analyzes the results of each research method and answers the above questions. Finally, Section 5 concludes this study and discusses the academic contributions and managerial significance, including the limitations and future research.

2. Literature Review

2.1. E-Commerce during the COVID-19 Pandemic

The COVID-19 pandemic alters social and customer behavior [14,27]. There has been a significant increase in the frequency of purchasing goods online during the pandemic [28]. Sales of some online product categories, such as electronics and fresh food, have increased dramatically [29]. Customer behavior patterns have also changed, showing a relatively stable and constantly evolving new pattern during the pandemic [30].

The pandemic was found to have significantly impacted e-commerce customers' opinions [31–33]. Managers of e-commerce need to deal with these opinion effects to improve their product and service capabilities and make their business sustainable [5]. However, this impact could change as the pandemic progresses. Chang and Meyerhoefer [4] found that customers used online shopping services heavily during the acute stage of the pandemic, but the ease of travel bans and movement restrictions reduced this trend. Han et al. [34] showed that the overall e-commerce sales in China dropped during the Wuhan lockdown, but they recovered as the government gradually relaxed its movement restrictions.

In general, COVID-19 and corresponding control measures contributed to a significant increase in e-commerce sales in many countries [35–37], and it is a catalyst for e-commerce development [38]. E-commerce satisfies customers' demand for goods during limited movement and social distancing [39]. It also helps brick-and-mortar businesses build resilience against the impact of the pandemic [40] and accelerate direct exporting [41]. In importing countries, e-commerce development contributed to mitigating the adverse effects of the pandemic [42].

In essence, current studies have elucidated shifts in customer perceptions throughout the pandemic, predominantly focusing on buying intent and satisfaction evaluations, with questionnaires being the principal data source. Yet, a detailed examination of the nuanced alterations in product and service attributes, as discerned through online reviews, remains unexplored. Building upon the foundation laid by these studies, this research employs online reviews to perform a nuanced pre-and-during pandemic comparative analysis of fresh food e-commerce customer opinions. This approach facilitates an in-depth investigation into the change intricacies of product and service attributes, thereby uncovering the evolution of customer expectations and preferences.

2.2. Fresh Food E-Commerce Customer Satisfaction

Drastic changes have been brought about by the Internet and e-commerce growth in the traditional fresh food market. Suppliers and retailers are scrambling to open online channels to reach more customers. Some researchers have studied fresh food e-commerce customer satisfaction to enhance their development and improve their business. Based on online reviews, Guan et al. [16] identified the potential factors that may influence fresh food e-commerce customer satisfaction. Lin et al. [43] developed a questionnaire and explored the influence mechanism of e-commerce platform factors and product factors on customers' repurchase intention to enhance online fresh food customer satisfaction and increase the repurchase rate. The authors found that a significant impact exists between the product and platform factors and the perceived value of online fresh food customers. Customer satisfaction affects the degree of customer trust in online food shopping, which significantly impacts customer loyalty to fresh food e-commerce [44]. Customers' satisfaction evaluation of fresh food on the e-commerce platform also affects other customers' choices [45]. Ma et al. [46] found that production, customer service, product packaging, and customer benefits enhance fresh food customer satisfaction and drive their loyalty, and the post-purchase experience is also significant in gaining customer satisfaction. Jiang et al. [47] found that personal contact, timeliness, and empathy positively impact customer satisfaction with fresh food logistic services.

2.3. Measuring Customer Satisfaction Based on Online Reviews

Measuring customer satisfaction is vital for companies, as it can facilitate marketing analysis, customer behavior analysis, and product or service improvement [48–50]. The traditional way to measure customer satisfaction is to design a questionnaire survey. However, the quality of the questionnaire survey depends on the rationality of the question design and the respondents' willingness to be surveyed [51]. A statistical sampling method relying on a questionnaire may bring good data quality, but sometimes it involves biased selection, which makes the results lack universality. In the era of e-commerce, customers write online reviews to evaluate products or services spontaneously, which can be a data source for understanding customers [52,53]. Many researchers have attempted to understand customer satisfaction through online reviews to promote product or service improvement in different industries [20,25,54]. Some researchers have also studied how to evaluate customer satisfaction from online reviews and proposed some effective methods. For example, Bi et al. [18] proposed an integrated approach that combined machine learning techniques with an effect-based Kano Model for evaluating customer satisfaction from online reviews. Ahani et al. [55] developed a new approach based on multi-criteria decision-making and soft computing to determine satisfaction among travelers.

Different customers may have different preferences and expectations for products or services. Therefore, customer satisfaction varies among them [55,56]. Considering that customers with different cultural backgrounds think and behave differently, Jia [57] compared the restaurant satisfaction of Chinese and Americans to understand their different intentions and expectations. Darko and Liang [21] used self-organizing map clustering to segment customers based on their preferences and evaluated their satisfaction with the result of segmentation. Customer satisfaction or preference could change over time. Taking into account when online reviews are posted, customer satisfaction at different time periods can be obtained, which can be used to predict future customer satisfaction [58–60]. The direction of product–service improvement in the next stage can be obtained by analyzing the changing trend of customer satisfaction [61,62].

Owing to the long duration and broad impacts of the COVID-19 pandemic, customer behavior and decision-making have been affected. Existing research has studied the impact of COVID-19 on customer satisfaction in hotels and restaurants using online user-generated content [63–68]. Few studies have investigated the changes in customer opinion of e-commerce before and during the COVID-19 pandemic from online reviews, particularly fresh food e-commerce. Therefore, the present study aims to reveal such changes based on online reviews and provide insights into fresh food e-commerce to optimize resource allocation and improve customer satisfaction during a crisis.

3. Methodology

This study investigated the changes in customer expectations and preferences of fresh food e-commerce customers from online reviews. Figure 1 describes the text mining methodology used in this study. This study uses Python to collect and pre-process online reviews, which are available publicly on the website. Second, the product–service attributes of fresh food e-commerce were extracted through the K-means clustering method based on term frequency and inverse document frequency (TF-IDF) and singular vector decomposition (SVD). Third, the dictionary of product–service attributes is constructed to analyze the changes in customers' attention to the service attributes of each product in online reviews. Next, a product–service sentiment dictionary is constructed to calculate customer satisfaction with each product–service attribute in online reviews. Finally, the CIPA model was used to analyze customer attention and satisfaction changes and the corresponding product and service optimization strategies during the pandemic.

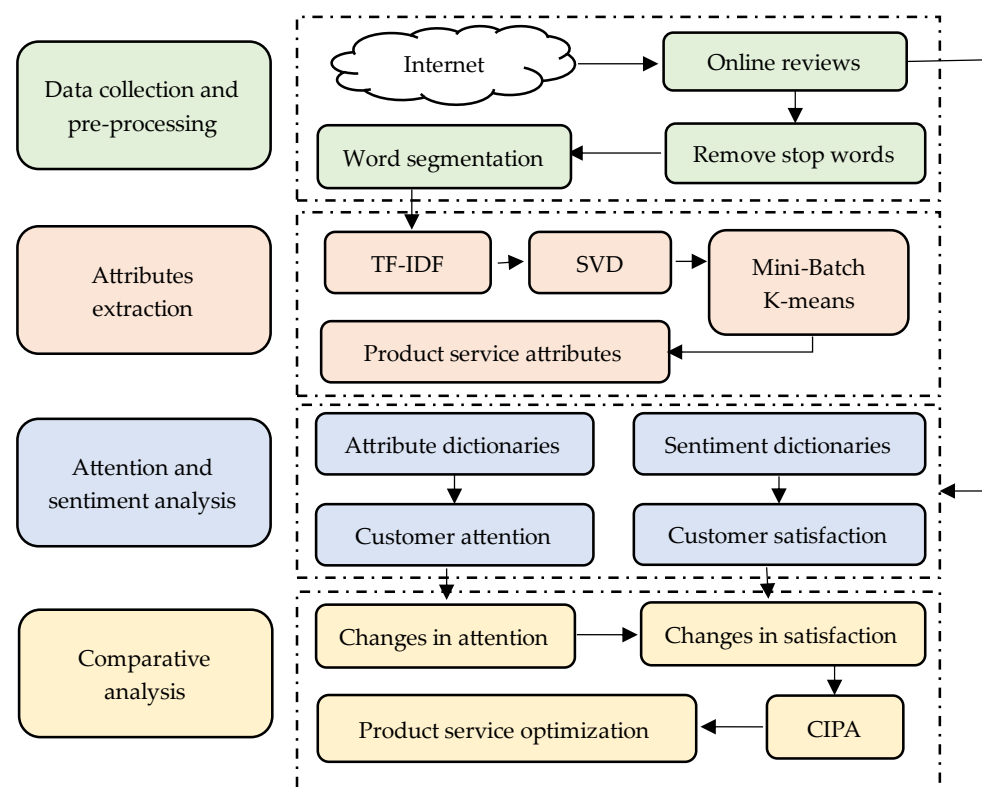


Figure 1. The text-mining methodology of this study.

3.1. Data Collection and Pre-Processing

According to China's Action against the Novel Coronavirus Outbreak (http://www.gov.cn/zhengce/2020-06/07/content_5517737.htm (accessed on 7 June 2020)), on 19 January 2020, the Chinese government confirmed that the coronavirus is spreading from person to person. With the efforts of the government and people, in Hubei Province, the worst-hit province, 97.5% of the supermarkets resumed work on 30 March 2020. Offline activities across the country have also resumed. Moreover, this study selected online reviews of fresh food e-commerce in China from 20 January 2020 to 30 March 2020, to ensure that the majority of fresh food e-commerce customers are affected by the COVID-19 epidemic. To conduct a more precise analysis of customer opinion changes in fresh food e-commerce products and services during the pandemic and mitigate potential seasonal influences, we also chose 20 January 2019 to 30 March 2019 as a reference period.

The primary purpose of this study is to understand the changes in preferences and expectations of fresh food e-commerce customers during the COVID-19 epidemic, particularly during the travel restrictions imposed by the government. As the number of new cases decreased at different stages of the pandemic, the government gradually eased travel restrictions. Social life and production order are progressively restored. In this scenario, customers' expectations and preferences may differ from those during the acute phase of the pandemic [63]. Therefore, this study divides the pandemic phase into two periods for discussion to distinguish the acute and remission phases.

The acute phase is from 20 January 2020 (the second day after the government announced the existence of human-to-human transmission of the coronavirus) to 17 March 2020 (the peak of the current pandemic has passed, the number of new cases continues to decline, and the pandemic remains at a low level (http://www.gov.cn/zhengce/2020-06/07/content_5517737.htm (accessed on 7 June 2020))), which represents the most severe phase of the pandemic. Furthermore, the recovery phase is from 18 March 2020 to 30 March 2020, which represents the phase where the pandemic gradually alleviates and social life gradually returns to normal. Then, we segmented the 2019 data into

R-Acute (20 January 2019 to 17 March 2019) and R-Recovery phases (18 March 2019 to 30 March 2019) for comparison purposes.

In the end, we selected 35 fresh products with a total of 12,382 online reviews, 4839 in 2019 and 7543 in 2020 from Taobao.com. We established a Python program to collect online review data from Taobao.com. These reviews are freely available and publicly accessible. The selected products include fruits and vegetables, meat, aquatic food, and cold drinks. Table 1 shows detailed information about the number of collected data.

Table 1. Number of online reviews of different periods.

	R-Acute	R-Recovery	Acute	Recovery
Overall	3879	960	6270	1273
Fruits and vegetables	1472	509	1890	355
Meat	742	158	1398	245
Aquatic food	1446	213	2027	410
Cold drinks	219	80	955	263

To facilitate the following data analysis, the data of the existing collected online review set should be pre-processed. The first step of pre-processing is to segment online reviews using the Jieba toolkit. Jieba toolkit is a widely used Chinese word segmentation toolkit. This study uses the toolkit to segment each online review into individual words or phrases. For example, “Good customer service, fast delivery” is segmented into “good/customer service/fast/delivery”. Then, through browsing the online reviews set we collected, we added some meaningless words, such as product names, to the Chinese stop words list. This word list is utilized to remove stop words from the online reviews set.

3.2. Extract the Product–Service Attributes of Fresh Food E-Commerce

The Mini-Batch K-means text clustering method based on TF-IDF and SVD is used in this study to answer the first research question. We chose this method because it is widely used and effective for feature extraction [69]. First, TF-IDF is used to represent the review text. TF-IDF is a text mining technique that can numerically represent online review text by reflecting the importance of a word in the online review set. Second, considering that the dimensionality of vectorized results of TF-IDF is too high, dimension compression technology can be used for processing. SVD is used in this study to process the vectorized results. The vectorized results X can be decomposed into three other matrices multiplied together and are described in Equation (1). Specifically, U and V are orthogonal matrices of left and right singular vectors, respectively. Σ is a diagonal matrix of singular values, which is the square root of the eigenvalues of matrices U or V .

$$X = U \times \Sigma \times V^T. \quad (1)$$

After using SVD to reduce the dimension of the vectorized results, the Mini-Batch K-means cluster algorithm, which is an optimization variant of the K-means algorithm, is used to cluster the vectorized results to keep the accuracy of clustering as far as possible while reducing the calculation time. The Mini-Batch K-means cluster algorithm can extract high-frequency words in each clustering result. Finally, according to the high-frequency words, the product–service attributes described by each clustering result can be named by researchers. The set of product–service attributes is denoted as $A = \{A_l | l \in [1, L]\}$, where A_l represents the l th product–service attribute.

3.3. Customer Attention Analysis Based on Attribute Dictionary

Based on the extracted product–service attributes, an attribute dictionary can be built to identify the attributes involved in each online review. The attribute dictionary can be based on the high-frequency words shown in the above cluster results and related words added by researchers browsing online reviews. Online review text usually consists of several

sentences, each of which may contain customers' evaluation information about a different attribute. When evaluating different attributes, customers tend to use punctuation marks for segmentation. For example, a "Good customer service, fast delivery" review includes evaluations of different attributes, separated by commas. Therefore, the researchers split an online review into one or several short sentences based on punctuation. We assume that multiple review sentences about the same attribute can be combined into one sentence and represent the attitude of this online review toward that attribute. In summary, we use the attribute dictionary to group these sentences into different groups. We use the sentiment group to evaluate this online review toward each attribute and think that this represents this customer paying attention to this attribute. Let the number of grouped short sentences of attribute A_l be denoted as G_l . Let the total number of collected online reviews be denoted as D . And then, we can know the degree of customer group's attention CA_l to the attribute A_l . CA_l can be calculated as Equation (2):

$$CA_l = \frac{G_l}{D}. \quad (2)$$

3.4. Sentiment Analysis Based on Sentiment Dictionary

After extracting the attributes and customer attention analysis of fresh food e-commerce, an attribute-level sentiment analysis technique is needed to assess customer satisfaction on each attribute. This study uses the lexicon-based sentiment analysis method for attribute-level sentiment analysis. The specific process is constructed as follows [70,71]:

- (1) Compiling a dictionary of sentiment words. A sentiment dictionary is used to identify the sentiment polarity expressed by customers about the attributes included in online reviews. Sentiment words are words with evident emotional tendencies, such as happiness and depression. This study divides emotional polarity into three poles: positive, negative, and neutral. A collection of sentiment words constitutes a sentiment dictionary. The sentiment dictionary is mainly based on the commonly used HowNet Sentiment Dictionary and Taiwan University Sentiment Dictionary [72]. The emotional polarity of a word can be marked as follows:

$$P(S_{dn}) = \begin{cases} 1, & \text{if } S_{dn} \in C^+ \\ 0, & \text{if } S_{dn} \in C \\ -1 & \text{if } S_{dn} \in C^- \end{cases}. \quad (3)$$

where C^+ , C , and C^- represent the sentiment dictionaries of the words with positive, neutral, and negative polarity, respectively. S_{dn} is the n th sentiment word in a grouped short sentence S_d of one attribute. $P(S_{dn})$ refers to the polarity of the sentiment word S_{dn} .

- (2) Constructing a degree adverb dictionary. Consumers often use adverbs of degree in reviews to reflect their emotional intensities. For example, "I kind of like this product" and "I like this product a lot" express different sentiment intensities. Using the adverbs of degree collected by HowNet, a dictionary of adverbs of degree is constructed in this study. Adverbs of degree are assigned a score of 1.5 or 2 according to the sentiment intensity expressed by the customers who use them.
- (3) Constructing a dictionary of negative words. The dictionary of negative words contains negative words commonly used in online reviews. Negative words are collected by browsing online reviews. The impact of a sentence with a negative word is the opposite of the original polarity of the emotional word. Therefore, the weight of negative words is set to -1 . Hence, the number of negative words located before the sentiment word S_{dn} is defined as q , and the impact of these negative words is defined as $[(-1)_{dn}]^q$.
- (4) Calculating the sentiment score. According to the above short sentences extracted from each online review, dictionaries of emotional words, degree adverbs, and negative

words, the customer's sentiment polarity for a particular product–service attribute can be calculated. Sentiment value V_{dl} with respect to A_l can be calculated as follows:

$$V_{dl} = \sum_{i=1}^n P(S_{dn}) \times \text{mul}(S_{dn}) \times [(-1)_{dn}]^q. \quad (4)$$

Then, customer satisfaction and evaluation scales are obtained according to the sentiment values. E represents the set of evaluation scales of customer satisfaction, and $E = \{E^1 = 1, E^2 = 2, E^3 = 3\}$. E^λ refers to the λ th evaluation scale, and $\lambda = 1, 2, 3$, where E^1 , E^2 , and E^3 represent dissatisfaction, neutral, and satisfaction, respectively. Therefore, the definition of E is shown as follows:

$$E = \begin{cases} 1, & V_{dl} < 0 \\ 2, & V_{dl} = 0. \\ 3, & V_{dl} > 0 \end{cases}. \quad (5)$$

- (5) Calculating the overall customer satisfaction for each attribute. The number of online reviews whose satisfaction evaluation scale of A_l is E^λ is recorded as G_l^λ . Then, the probability that the satisfaction evaluation scale of A_l is E^λ is defined as follows:

$$POG_l^\lambda = \frac{G_l^\lambda}{G_l}. \quad (6)$$

According to Equation (7), the overall customer satisfaction CS_l of A_l is as follows:

$$CS_l = \sum_{\lambda=1}^3 POG_l^\lambda E^\lambda. \quad (7)$$

3.5. Comparative Analysis

Importance–performance analysis (IPA), proposed by Martilla and James [73], is a technique for improving the quality of products and services. It was widely used to test the attribute importance and performance of hotel services [74], public transport services [2], and airport services et al. [75], to enhance customer satisfaction. Generally, customer satisfaction is used as an indication of attribute performance. As shown in Figure 2, in the IPA analysis, the importance and satisfaction of the research object are two dimensions that establish a four-quadrant graph. The abscissa is the customer satisfaction with product or service attributes, and the ordinate is the importance that the customer assigns to the product–service attributes. The quadrants are divided according to the mean satisfaction and mean importance of each attribute. Quadrant 1 contains attributes with high importance and satisfaction. Attributes located in quadrant 2 represent the high importance of attributes but customer satisfaction is low. These attributes require further improvement. Attributes located in quadrant 3 represent the low importance and satisfaction, which may also contain opportunities for innovation and improvement. Attributes that fall in quadrant 4 have the lowest improvement priority, due to their low importance and high satisfaction.

Hu et al. (2021) [63] proposed a revised CIPA model to reveal the impact of the COVID-19 pandemic on hotel service customer assessments by calculating the difference between the importance and satisfaction of attributes in CIPA and the reference period. In this study, CIPA was used to analyze the changes in attention and satisfaction of fresh food e-commerce customers caused by the COVID-19 pandemic and to obtain insights that can help fresh food e-commerce to product and service optimization. The change in attention that represents the importance difference AI_l and the change in satisfaction that represents performance difference PI_l can be calculated as Equations (8) and (9), respectively, where

CA_l^T represents the mean of customer attention of attribute A_l overall periods and CS_l^T represents the mean of customer satisfaction of attribute A_l overall periods.

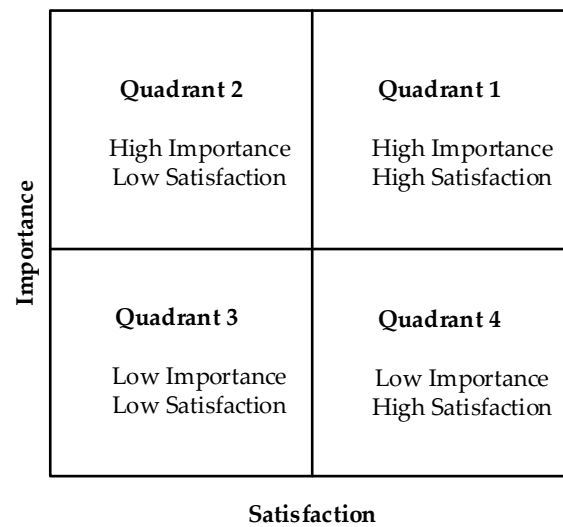


Figure 2. IPA.

$$AI_l = \frac{CA_l - CA_l^T}{CA_l^T}, \quad (8)$$

$$PI_l = \frac{CS_l - CS_l^T}{CS_l^T}. \quad (9)$$

As shown in Figure 3, the X-axis records the change in attribute attention, and the Y-axis records the change in performance evaluation. It is divided by zero shift in attention and zero change in performance evaluation. “CIPA grid” divides fresh food product–service attributes into four quadrants. Each of the four quadrants has different strategic implications.

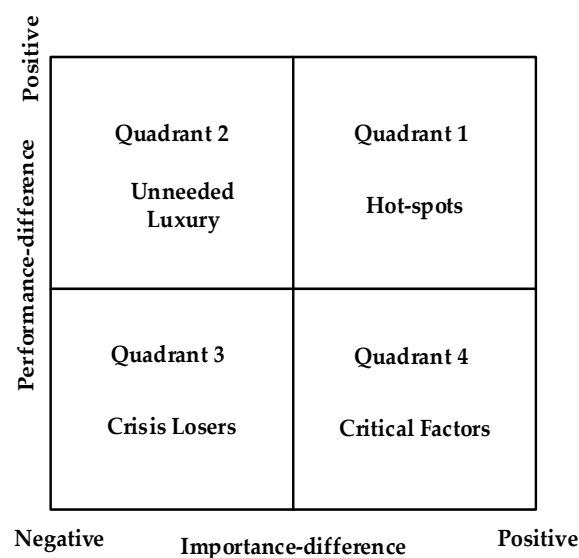


Figure 3. CIPA.

- (a) “Hot Spots”. Attributes in this quadrant mean they have increased in importance and performed better during the crisis, and they are the strengths of increased importance. Fresh food e-commerce should maintain these better performances during a crisis.

- (b) “Unneeded Luxury”. Attributes in this quadrant mean they performed better but were less important during the crisis. These attributes are the strengths of decreased importance in the crisis. Fresh food e-commerce does not need to pay much attention to these attributes.
- (c) “Critical Factors”. Attributes in this quadrant have increased in importance but decreased performance during the crisis. These attributes are weaknesses of the increased importance of fresh food e-commerce products and services that need to be focused on and improved to satisfy customers during a crisis better.
- (d) “Crisis Losers”. Attributes in this quadrant mean their importance and performance decreased during the crisis and are the weakness of decreased importance. Therefore, these deficiencies of fresh food e-commerce need not be addressed as a high priority, compared with “Critical Factors”.

4. Results

4.1. Attribute Identification

In this study, we utilized Python to implement TF-IDF, SVD, and K-means clustering analysis of the collected online reviews. The appropriate number of clusters of the K-means method is first selected according to the sum of the squares of errors in clusters (SSE). As shown in Figure 4, after the number of clusters is 6, SSE drops more slowly with the increase in clusters. However, we tested other cluster numbers, from 6 to 19. The results show that when the number is less than 13, fewer attribute numbers can be analyzed through clustering results, while when the number is more than 13, only repeated attributes are added. Therefore, the appropriate number of clusters we choose is 13.

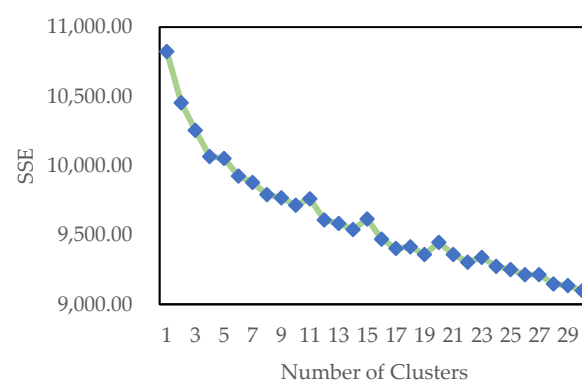


Figure 4. SSE of Mini-Batch K-means algorithm.

Table 2 presents the clustering results by setting the number of clusters to 13. The researchers named clusters according to the high-frequency words in each cluster. The first, ninth, and tenth clusters all describe freshness-related topics, so we grouped them into one attribute named freshness. The fifth cluster named returned customer, the sixth cluster named overall quality, and the eleventh cluster named epidemic are weakly associated with specific product or service attributes, so we deleted these three topics. Finally, eight attributes are obtained: freshness, shipping speed, product specifications, delivery speed, logistic packaging, service attitude, taste and mouthfeel, and cost performance. From these eight attributes, customers’ evaluation of fresh food e-commerce products and services includes logistic service, customer service, and the product itself. Shipping speed, delivery speed, and product packaging are logistic service-related attributes. Product specification, freshness, cost performance, and taste and mouthfeel are product-related attributes. Service attitude is a customer service-related attribute.

Table 2. High-frequency words of K-Means algorithm.

Cluster Number	Attribute	High-Frequency Words
1	Freshness	Date, fresh, packing, deliver goods, Shun Feng, supermarket, ice pack, commodities, taste, price
2	Shipping speed	Express delivery, special, merchant, shipping goods, come back, ice pack, taste, pictures, pack
3	Product specifications	Size, very big, fresh, pretty big, not small, uniform, taste, will again, soon, packing
4	Delivery speed	Logistics, the period, soon, fresh, express delivery, deliver goods, taste, packing, Shun Feng, speed
5	Returned customer	Have bought, last year, a few times, twice, fresh, butter, online, last time, this house, taste
6	Overall quality	Quality, fresh, deliver goods, price, packing, good value, logistics, be worth, a seller, soon
7	Logistic packaging	Packing, deliver goods, fresh, taste, quality, ice pack, express delivery, strict, in good condition
8	Service attitude	Customer service, attitude, service attitude, deliver goods, solve, express delivery, service, patience, reply, time
9	Freshness	Super, fresh, deliver goods, packing, special, taste, logistics, evaluation, service, period
10	Freshness	Fresh, special, very tender, taste, be worth, express delivery, will again, Shun Feng, deliver goods, picture
11	Epidemic	The epidemic, a period of time, deliver goods, express delivery, hard work, a supermarket, soon, logistics, an ice pack, understand
12	Taste and mouthfeel	Taste, mouthfeel, fresh, price, special, be worth, authentic, a piece, a child, will
13	Cost performance	Cost performance, cheap, specifications, taste, express delivery, logistics, taste, soon, fresh, very big

4.2. Changes in the Importance of Attributes

To obtain the importance changes in attributes, we first build the attribute dictionary. Table 3 shows some attribute words. Second, according to Equation (2), the importance of attributes was calculated. The standardized results of importance are obtained according to Equation (8). Appendix A, Table 4, and Table 5 show the number of grouped sentences of each attribute, the importance results of attributes, and standardized results of importance, respectively.

Table 3. Attribute dictionary (part).

Attributes	Attribute Word
Freshness	Fresh, rotten, bad, smell bad, metamorphism, tender. . .
Shipping speed	Shipments, deliver service of seller, send
Product specification	Specifications, sufficient weight, huge, size, uniform, full. . .
Delivery speed	Express delivery, CaiNiao, post station, logistics, transportation, dispatch. . .
Logistic packaging	Packing, strict, bubble, appearance, carton, firm. . .

Table 3. Cont.

Attributes	Attribute Word
Service attitude	Customer service, service, attitude, reply to warm-hearted, refreshing. . .
Taste and mouthfeel	Taste, mouthfeel, delicious, taste, incense, spicy. . .
Cost performance	Cost performance, cheap, good value, promotion, cost-effective, expensive. . .

Table 4. Importance results of product–service attributes.

Attributes	Freshness	Shipping Speed	Product Specification	Delivery Speed
R-Acute	0.2514	0.0351	0.1645	0.1982
R-Recovery	0.2646	0.0323	0.1458	0.1708
Acute	0.2309	0.0625	0.1663	0.2498
Recovery	0.2726	0.0573	0.1940	0.2372
Attributes	Logistic Packaging	Service Attitude	Taste and Mouthfeel	Cost Performance
R-Acute	0.1057	0.0835	0.2743	0.1165
R-Recovery	0.0979	0.0698	0.3458	0.1052
Acute	0.1404	0.0807	0.4105	0.1469
Recovery	0.1312	0.0848	0.4305	0.1453

Table 5. Standardized importance results of product–service attributes.

Attributes	Freshness	Shipping Speed	Product Specification	Delivery Speed
R-Acute	−0.0138	−0.2509	−0.0191	−0.0737
R-Recovery	0.0381	−0.3101	−0.1302	−0.2018
Acute	−0.0939	0.3358	−0.0079	0.1670
Recovery	0.0695	0.2252	0.1572	0.1085
Attributes	Logistic Packaging	Service Attitude	Taste and Mouthfeel	Cost Performance
R-Acute	−0.1102	0.0478	−0.2491	−0.0931
R-Recovery	−0.1757	−0.1245	−0.0532	−0.1812
Acute	0.1815	0.0124	0.1239	0.1432
Recovery	0.1044	0.0643	0.1785	0.1311

Table 4 shows that “taste and mouthfeel” is the most important attribute, which gained the most customer attention in all periods, maybe because the primary function of fresh food is to satisfy consumers’ taste buds. Shipping speed has the least importance, possibly because consumers were not as focused on this attribute before and after the pandemic. Moreover, the industry has an unwritten convention for shipping speed (i.e., shipping within 48 h).

Figure 5 visualizes the results of standardized importance to show the changes in attributes’ importance in the four time periods. The positive (negative) value of standardized importance means this attribute gained (lost) importance in a certain period. In Figure 5, it can be seen that a significant difference exists in the change value of attributes’ importance.

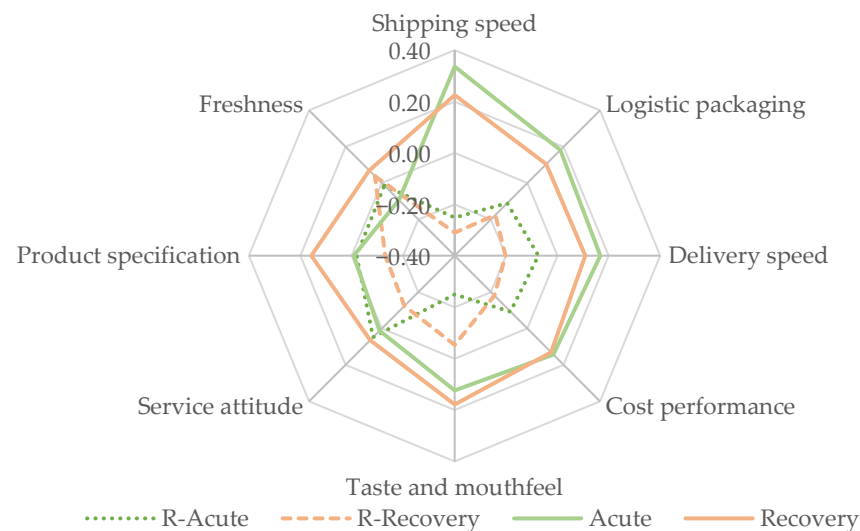


Figure 5. Changes in attributes' importance before and after COVID-19.

Notably, the importance of freshness decreased in the acute period, indicating the customers' loss of interest in this attribute due to a limited supply of goods due to the pandemic. Conversely, some attributes (e.g., delivery speed, logistic packaging, and taste and mouthfeel) gained importance during the pandemic. The importance of shipping speed and delivery speed has increased significantly, which may be caused by the lower logistic capacity than usual caused by government controls during the pandemic. Moreover, customers are paying more attention to this. The importance of logistic packaging has also increased, possibly because the integrity and hygiene of logistic packaging can reduce the probability of virus transmission, and customers have become more concerned during the pandemic.

Unexpectedly, all attributes gained importance during the recovery phase. However, the importance of logistic service-related attributes (shipping speed, logistic packaging, and delivery speed) decreased compared with the acute phase. The reason may be the recovering capacity caused by the eased government control and fewer cases during the recovery phase, which resulted in less concern for these attributes. Some product-related attributes (taste and mouthfeel, product specification, and freshness) have increased in importance compared with the acute phase. This result reflects that customers are starting to focus on the product itself, rather than some logistics (shipping speed, logistic packaging, and delivery speed).

4.3. Changes in Customers' Performance Assessments

Customer satisfaction is used to investigate customers' performance of fresh food e-commerce. The sentiment expressed by customers is obtained through the method in Section 3.4. Table 6 shows the sentiment analysis results. The values of customer satisfaction (attribute performance) CS_i calculated in Equation (7) are shown in Appendix B. We standardized the achieved attribute performance for comparison analysis and displayed the results of standardized customer satisfaction in Table 7. Figure 6 visualizes the significant changes in customers' performance assessment over time according to the value of standardized customer satisfaction. A positive (negative) value of standardized customer satisfaction represents a more positive (negative) evaluation of a single attribute in a certain period, indicating an improvement (decline) in attribute performance.

Table 6. Sentiment analysis results of product–service attributes.

Period	Polarity	Freshness	Shipping Speed	Product Specification	Delivery Speed
R-Acute	1	165	15	74	106
	2	119	27	229	306
	3	691	94	335	357
R-Recovery	1	37	4	24	19
	2	28	9	43	60
	3	189	18	73	85
Acute	1	240	62	126	219
	2	223	92	394	551
	3	985	238	523	796
Recovery	1	81	17	18	57
	2	47	11	94	120
	3	219	45	135	125
Attributes	Polarity	Logistic Packaging	Service Attitude	Taste and Mouthfeel	Cost Performance
R-Acute	1	32	29	66	72
	2	101	74	169	87
	3	277	221	829	293
R-Recovery	1	10	5	28	23
	2	29	19	55	20
	3	55	43	249	58
Acute	1	96	53	178	138
	2	257	142	490	211
	3	527	311	1906	572
Recovery	1	23	15	58	24
	2	44	30	107	38
	3	100	63	383	123

Table 7. Standardized performance results of product–service attributes.

Attributes	Freshness	Shipping Speed	Product Specification	Delivery Speed
R-Acute	0.0107	0.0465	0.0024	−0.0018
R-Recovery	0.0342	−0.0059	−0.0222	0.0308
Acute	0.0008	−0.0070	−0.0095	0.0162
Recovery	−0.0457	−0.0335	0.0293	−0.0452
Attributes	Logistic Packaging	Service Attitude	Taste and Mouthfeel	Cost Performance
R-Acute	0.0362	0.0253	0.0208	0.0041
R-Recovery	−0.0112	0.0153	0.0015	−0.0239
Acute	−0.0068	−0.0074	0.0036	−0.0030
Recovery	−0.0182	−0.0333	−0.0258	0.0228

In Figure 6, the attribute performance difference (e.g., cost performance, packaging, and delivery speed) of pre-COVID-19 periods exhibit some seasonal effects, which impact customers' performance assessment. The reason may be in the R-Recovery phase, compared with the R-Acute phase, the warmer weather made customers have higher requirements for these attributes. However, differences exist in customers' performance evaluation of attributes during these periods.

In general, during the acute phase, the performance values that customers evaluated were close to the average over four periods. This case indicates that customers did not respond strongly to the performance of attributes and showed greater forgiveness

on most attributes (e.g., delivery speed, taste and mouthfeel, and freshness) during the pandemic. Customers complained about some attributes (e.g., service attitude, shipping speed, and product specification) but to a lesser extent. The reason may be customers' understanding of the difficulty in maintaining good performance in these attributes during the acute phase.

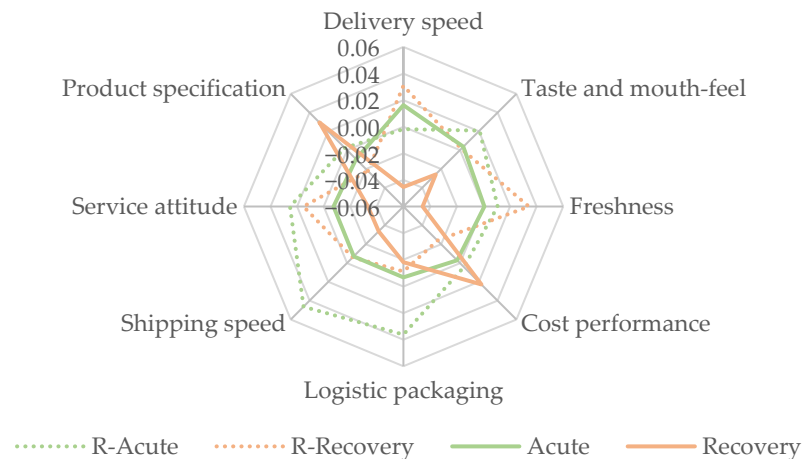


Figure 6. Changes in attribute performance across dynamics.

Attributes (e.g., logistics speed, taste and mouthfeel, delivery speed, and service attitude) that showed significant declines in performance evaluation during the recovery phase indicated that fresh food e-commerce was unable to meet customers' expectations for these attributes. During the acute phase, customers can forgive or expect less of these poor performances, but customer discontent was displayed during the recovery phase. Logistics service-related attributes and product freshness received poor ratings, and customer expectations for these increased compared with the acute phase. Moreover, the product cost performance and specifications have been higher evaluations.

4.4. Product–Service Optimization for Crises

CIPA was conducted and shown in Figure 7 to obtain management measures for product–service optimization during crises such as a public health emergency. In Figure 7, customers' evaluations of the attributes' importance and performance during the two phases of the pandemic were compared by jointly analyzing the difference in importance and performance. The average importance and performance weights of each attribute of the four time periods serve as the reference according to Equations (8) and (9) [63]. The acute and recovery phases are also compared in Figure 7. The horizontal distance between two points of one attribute represents the change in importance of the two phases, and the vertical distance represents performance differences existing in the two pandemic phases.

Focusing on the acute period, service attitude, cost performance, logistic packaging, and shipping speed gained importance but lost customer satisfaction and were “critical factors” during the pandemic. This finding highlights customers' acute need for these attributes, which fresh food e-commerce could not successfully address. Delivery speed and “taste and mouth-feel” were rated more positively and considered more important, making them appear to be “hot-spots” during the pandemic. The reason may be that the pandemic has severely affected logistics capacity and the availability of fresh food. Customers pay more attention to these attributes but have a higher tolerance for their performance. In addition, the efforts made by fresh food e-commerce in the logistic service can adapt to the changes in customer needs. Freshness was the pandemic's “unneeded luxury” with decreased importance and increased performance. Fresh food e-commerce was able to improve their freshness to meet customer expectations during the pandemic, but customers considered this attribute less important. Freshness will not be a priority for improvement. Product specification was pandemic “crisis losers”, which lost importance and performance

during the acute phase. Customers might have recognized and shown some forgiveness to the limitations of fresh food e-commerce to improve the product specification setting to meet customer requirements.

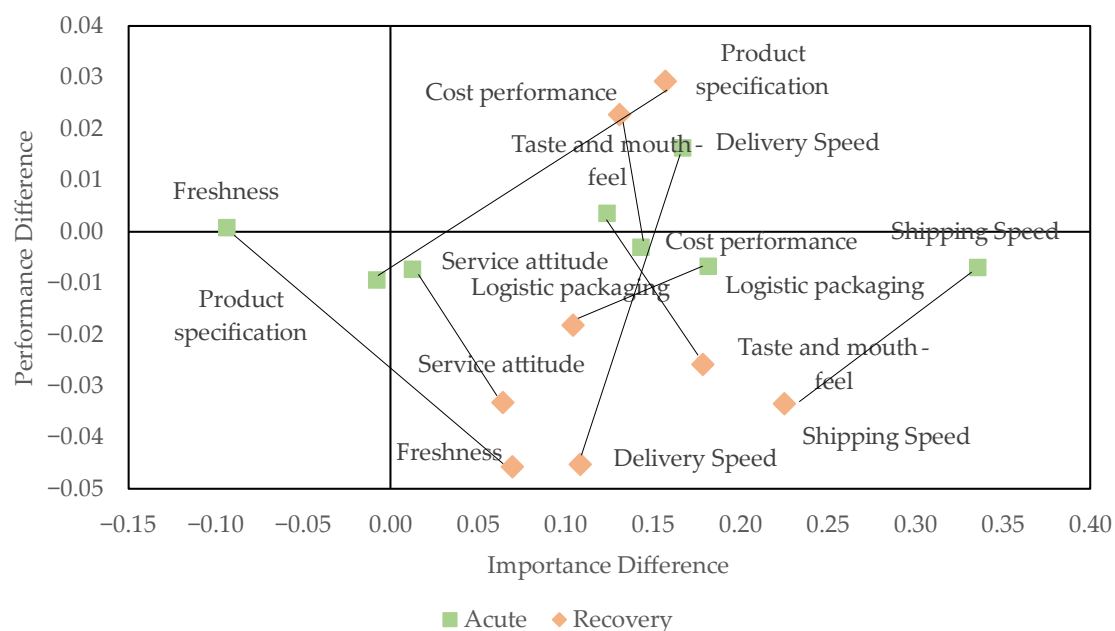


Figure 7. Results of CIPA.

Significant differences exist regarding the attribute performance and importance between the acute and recovery phases. Several attributes (e.g., service attitude, freshness, delivery speed, shipping speed, and taste and mouthfeel) are moved down from the position of the acute period and were the “critical factor” of the recovery phase. This result indicates that e-commerce has not successfully adapted to the changing customer need for these attributes in the recovery period, or the high customers’ tolerance for service failure made by fresh e-commerce during the acute pandemic has been reduced. Fresh food e-commerce should strive to improve these attributes in the recovery phase. Freshness moved from “unneeded luxury” to “critical factors”. Fresh food e-commerce should allocate resources for freshness improvement for its increased importance and decreased performance. E-commerce has adjusted its product specification and cost performance attribute recovery during the recovery period and gained increased customer evaluation. Particularly, customer satisfaction with product specification increased, and this attribute moved from “crisis losers” to the “hot-spots” quadrant. This case exemplifies e-commerce successfully adapting to the changing customer need for product specification.

5. Discussions and Conclusions

Most prior research investigated the impact of the COVID-19 pandemic and provided suggestions for e-commerce managers or policymakers. The existing literature has attempted to understand customer purchase behavior on fresh food e-commerce products or services through surveys during COVID-19. However, few focus on the customer opinion change in fresh food e-commerce before and after the COVID-19 outbreak through online reviews. The current study investigated customer opinion changes before and during the COVID-19 pandemic to gain actionable insights for fresh food e-commerce managers. Online reviews provided a good source of data for understanding customer opinions. The findings of this study can assist in guiding fresh food e-commerce managers in allocating limited resources in the case of a sudden public health emergency and adapting to meet the ever-changing customer needs. This study has answered the four research questions.

First, regarding the product and service attributes of e-commerce that affect customers’ opinions, we find eight product–service attributes that customers commented on in the

online reviews through the text mining technique, K-means clustering method integrated TF-IDF, and SVD. The attributes are freshness, shipping speed, product specifications, delivery speed, logistic packaging, service attitude, taste and mouthfeel, and cost performance. These attributes also reflect customers' focus on logistics service, customer service, and products.

Second, regarding the changes in customers' perceptions of the importance of each attribute, we find that during the acute phase of the pandemic, shipping speed, logistic packaging, and delivery speed related to the logistic service of e-commerce gained increased customer attention, which is consistent with the conclusions from previous studies [16]. Moreover, product specification and freshness related to the product lost importance. However, during the recovery phase of the pandemic, compared with the acute phase, the importance of taste and mouthfeel, product specification, and freshness related to the product increased, and the importance of logistic service-related attributes, such as shipping speed, logistic packaging, and delivery speed, decreased. These results of the different attribute importance changes in the recovery phase compared with the acute phase extend previous research on consumer behavior regarding e-commerce in the background of COVID-19 [15,16,29].

Third, regarding the changes in customers' opinions on the product-service performance, we find that during the acute phase of the pandemic, customers show a greater level of forgiveness on many attributes, particularly for delivery speed, taste and mouthfeel, and freshness. Moreover, they evaluated the poor performance of the product-service attributes relatively positively. However, customer dissatisfaction toward logistic service-related attributes, customer service-related attributes, and freshness has been relatively fully expressed in the recovery phase of the pandemic. These findings also extend existing research. Previous studies have shown that COVID-19 has impacted customer experience or satisfaction in the fresh food e-commerce sector [16] or general online consumer purchasing [8,15]. In contrast, the findings of this study provide a more detailed insight into how satisfaction levels change and vary across different attributes during COVID-19.

Last, regarding the enlightenment for fresh food e-commerce to cope with the sudden pandemic, we conducted CIPA to form practical strategies to guide them to optimize their product and services. For instance, owing to the suddenness of the pandemic and the government's prevention and control measures, fresh food e-commerce needs to focus on and improve some attributes (e.g., cost performance, shipping speed, service attitude, and logistic packaging) during the pandemic, particularly the recovery phase, to achieve customer satisfaction.

5.1. Theoretical Implications

The theoretical implications of this study are mainly in the following two aspects. First, this study provides insights into customer perceptions regarding fresh food e-commerce. Through the use of text-mining techniques, this study identified eight key attributes that customers pay attention to and express their opinions on the logistic-related services, customer service, and the product itself. This study also found that among the eight attributes, "taste and mouth-feel" is the most important attribute, which gained the most customer attention in all periods, while shipping speed has the most minor importance.

Furthermore, this study delved into the changes in customer opinions at the attribute level, enriching and expanding the existing research on the ever-changing customer opinions of e-commerce. This study investigates the impact of the COVID-19 pandemic on fresh food e-commerce and compares the preferences and expectations to obtain customer opinion change before and during the pandemic. The findings of this study provide evidence that e-commerce customer opinions on product and service attributes can be changed due to the outbreak of acute pandemics, such as COVID-19 and the government's prevention measures alter customers' expectations for the products and services of fresh food e-commerce.

Finally, this study also found that during different stages of the pandemic, customer's focus and expectations also exhibited varying changes. For example, during the acute phase of the COVID-19 pandemic, due to customer concerns about the outbreak, attributes related to logistics services became the focal point of customer attention. This can be attributed to customers prioritizing the swift delivery of products during the pandemic. However, as the situation gradually came under control and recovery began, customers shifted their focus to attributes associated with the product itself. Customers began to pay more attention to the quality of products as the pandemic subsided, with people gradually regaining their focus on their dietary health and quality of life. This finding provides valuable insights for future research on e-commerce during pandemics, as discussions on different pandemic stages appear to be necessary.

5.2. Practical Implications

This study also has implications for management practice. For fresh food e-commerce, this study can help guide fresh food e-commerce's practice to prioritize its measures and adapt to possible changes in customer needs during pandemics through the results of CIPA. For instance, during the acute phase, the delivery speed gained more customer tolerance and was located in quadrant 1 as "good work". Customer attention to freshness was reduced in this phase, but it gained importance and lost performance evaluations in the recovery stage. Fresh food e-commerce managers can reduce attention to these attributes during the acute stage of the pandemic but must improve these products and services during the recovery period to avoid a decrease in customer satisfaction.

Service attitude, logistic packaging, and shipping speed need to gain higher priority to focus and improve during the pandemic periods. Cost performance and product specification should gain high priority to improve during the acute phase of the pandemic, but customers' performance evaluation increased during the recovery phase, indicating that customers' requirements concerning this attribute may return to normal. Products or services related to these two attributes need to be improved as much as possible to meet the increased requirement during the acute stage of the pandemic and can be relaxed during the recovery period. Fresh food e-commerce can temporarily reduce efforts to maintain the freshness of products during the acute period. However, during the recovery phase, the maintenance of freshness must be focused on.

This study can also help consumers better understand their own needs and continuously adjust their expectations for fresh food e-commerce during future severe pandemics, thereby reducing unnecessary disputes and conflicts arising from dissatisfaction with products and services due to force majeure. This study also encourages customers to write reviews expressing their opinions, thereby providing convenience for managers to understand the evolving customer needs. For the government, supporting businesses in meeting consumer needs at different stages is crucial. The government can provide guidance and support for the e-commerce of fresh food, promoting the effective operation of the industry during both the acute phase and the recovery phase of an epidemic while ensuring consumer rights and satisfaction. For example, establishing a safe, hygienic, and efficient logistics and storage system can ensure logistics' timeliness and products' freshness during the epidemic recovery period.

5.3. Limitations and Future Research

This study presents several limitations. First, online reviews are typically written by customers who are highly positive or negative, and certain demographic groups are more inclined to write reviews. Therefore, the collected data may lean toward the viewpoints of this particular group of people. Meanwhile, customers may have different expectations for e-commerce providers of various types of fresh food during the epidemic period. The failure to segment customers in this paper may overlook subtle differences in customer opinions. Second, online reviews may contain invalid data, such as fake reviews or reviews manipulated by competitors. Therefore, the lack of filtering out invalid comments is also a

limitation of this paper. Third, at present, there may be some evidence suggesting that the COVID-19 pandemic has come to an end. The conclusions of this paper may have limited practical implications for the current situation. However, the findings of this study can be utilized for future severe epidemic outbreaks and guide fresh food e-commerce and the government to improve relevant emergency plans for supplying fresh products during pandemic outbreaks.

Fourth, limited by e-commerce sites, the amount of data we can view and obtain is limited. The number of fresh food online reviews in 2019 was lower than that in 2020, which may be because of the impact on fresh food sales of the COVID-19 pandemic. Therefore, the number of online reviews collected for this study is also unevenly distributed between 2019 and 2020. Fifth, this study fails to subdivide fresh food e-commerce companies or categories. Customers' expectations of enterprises with different companies and different types of products may be inconsistent. Finally, online reviews used in this study were collected from a single website.

Future research may integrate online reviews with methods such as questionnaires and interviews to obtain more representative conclusions and capture the differences in perspectives among different demographic groups based on statistical characteristics. The inconsistency in the evaluation of different customers, different companies, or product categories of fresh food e-commerce with different data sources may also be considered in future research. Future research may also develop models to filter out invalid reviews and improve data quality. From the initial outbreak of the epidemic to China lifting all control policies, the development of the epidemic has gone through other various stages. During these stages, there may be specific trends and patterns in the changes in customer opinions. Exploring these patterns will also be an important focus of future research.

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

Appendix A Number of Grouped Sentences of Product–Service Attributes

Attributes	Freshness	Shipping Speed	Product Specification	Delivery Speed
R-Acute	975	136	638	769
R-Recovery	254	31	140	164
Acute	1448	392	1043	1566
Recovery	347	73	247	302
Attributes	Logistic Packaging	Service Attitude	Taste and Mouthfeel	Cost Performance
R-Acute	410	324	1064	452
R-Recovery	94	67	332	101
Acute	880	506	2574	921
Recovery	167	108	548	185

Appendix B Performance Results of Product–Service Attributes

Attributes	Freshness	Shipping Speed	Product Specification	Delivery Speed
R-Acute	2.5395	2.5809	2.4091	2.3264
R-Recovery	2.5984	2.4516	2.3500	2.4024
Acute	2.5145	2.4490	2.3806	2.3685
Recovery	2.3977	2.3836	2.4737	2.2252
Attributes	Logistic Packaging	Service Attitude	Taste and Mouthfeel	Cost Performance
R-Acute	2.5976	2.5926	2.7171	2.4889
R-Recovery	2.4787	2.5672	2.6657	2.4195
Acute	2.4898	2.5099	2.6713	2.4712
Recovery	2.4611	2.4444	2.5931	2.5315

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