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Research on the Evaluation of E-Commerce Cold Chain Food Consumption Based on Big Data

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Abstract

In response to the problems of low efficiency and high cost of offline questionnaires, lack of keyword-consumer attitude correlation in online comment analysis, and little help for optimization solutions, an opinion analysis and improvement evaluation model based on sentiment analysis and Latent Dirichlet Allocation (LDA) document topic generation model is proposed. Using cold-chain food as the research object, a custom Python program was used to crawl the online consumer reviews about cold-chain food from Jingdong, a mainstream Chinese e-commerce company. A total of 70,134 reviews were obtained, including 65,535 valid reviews, which were analyzed by the LDA topic model and SnowNLP sentiment analysis to obtain the influencing factors and specific scores that affect consumer satisfaction. Then the importance ranking of the influencing factors was obtained by combining the word frequency and scores. Finally, based on the rankings and the reasons generated, suggestions are made for developing products and services for cold chain food. From theory and practice, it provides a reference basis for developing cold chain technology and consumer behavior research.

Keywords: cold chain food, LDA topic model, sentiment analysis, online reviews

1. Introduction

With the rise of e-commerce platforms such as Jingdong and Tmall, the traditional consumer goods market has seen an impact. Among them, cold chain food, as one of the newly rising food categories, competition within the industry has gradually shifted from farmers' markets to online e-commerce platforms. Under this circumstance, consumer evaluation, as an online platform feedback channel for major manufacturers, need to be analyzed scientifically and rationally by enterprises, which can solve the problems of long consumption time, high labor cost and slow feedback of traditional questionnaires, and adapt to the new market environment more quickly.

Numerous Chinese scholars have recently researched consumer satisfaction with online reviews. Ma Fengcai et al. (2020) used word frequency statistics to explore the key elements influencing consumer satisfaction with fresh products on e-commerce platforms. The experimental results showed that the logistics situation and product quality had the most significant impact on satisfaction. Yang Jiajia (2021) used empirical analysis to investigate consumers' satisfaction with cultural artworks sold on e-commerce platforms, with the quality of the content of the paintings and calligraphy artworks and the authenticity of the masters being the most critical factors affecting consumer satisfaction. Zhang Xinxin (2021) analyzed customer satisfaction in economy hotels based on online reviews and concluded that influencing factors such as perceived value, room environment, service quality, different environments, and room comfort were significant factors affecting customer satisfaction. Zhao Shanyan et al. (2022) conducted an empirical analysis and countermeasure study on the impact of negative online reviews on consumers' purchasing behavior, connecting the results of online reviews with vendor behavior.

However, all of the above studies only categorized and analyzed the consumer reviews and did not rank the keywords of the reviews and examine their importance for product improvement. This situation reduces the practical significance of the studies. Based on those research gaps, this paper proposes a method for analyzing and improving research on product opinion based on sentiment analysis and the Latent Dirichlet Allocation (LDA) model, analyzing online reviews of cold chain food products, mining the relationship between their topics, keywords, and consumers' sentiment. Based on these results, keywords' importance is calculated, providing a specific theoretical basis and data support for manufacturers to improve their products.

2. Research Theory and Data

2.1 LDA Theme Model

The LDA model is a topic extraction model for modeling discrete datasets by modeling the topic of textual information and then providing a short description of the document, retaining the essential statistical information. This model can efficiently handle large data sets.

Researchers have used the model extensively because of its simplicity and effectiveness, selecting the topic for each document from the topic distribution and later extracting words from the corresponding word distribution in the topic, repeating until every word in the document has been extracted. Griffiths and Steyvers (2004) impose a Dirichlet prior distribution on the beta parameters, making the LDA model a complete generative model. Yang Cheng et al. (2020) used the LDA model and sentiment analysis to calculate themes and scores based on data from mobile phone reviews to derive a methodology for mobile phone improvement analysis. Yang Xiuzhang et al. (2021) used an LDA model with a fused domain lexicon to analyze public opinion on Guizhou attractions. This paper uses an LDA topic model to classify topics and extract keywords for SK-II skin care product reviews.

2.2 Sentiment Analysis

Sentiment analysis (sentiment analysis), also known as opinion mining, includes elements such as sentiment classification and sentiment mining and is an analytical method that helps researchers to obtain users' sentiment direction, which can be currently classified into a manual formulation, machine learning, hybrid systems, and other categories. Sentiment analysis was first proposed by Hatzivassilglou (1997). Zhang Ziqiong et al. (2010), based on the sentiment analysis of product reviews on the Internet, described the primary content, standard methods and research progress of review chapters, word praise and depreciation, and utterances. Based on online reviews, Yan Qiang and Meng Yue (2013) proposed a model of factors influencing the perceived usefulness of online reviews and validated it. Xie Lixing et al. (2012) proposed a multi-strategy sentiment analysis framework based on the hierarchical structure to improve the classification effect. Banerjee (2017) argued that the usefulness of a review is influenced by the characteristics of the reviewer itself, including positivity, engagement, experience, reputation, competence, and sociality. In this paper, sentiment analysis is performed using SnowNLP, a method that compares each word in the acquired reviews with a standard corpus, aggregates the positive and negative probabilities of each review, and thus distinguishes positive reviews from negative reviews of the product.

2.3 Research Process

The process of research is as shown in the figure.

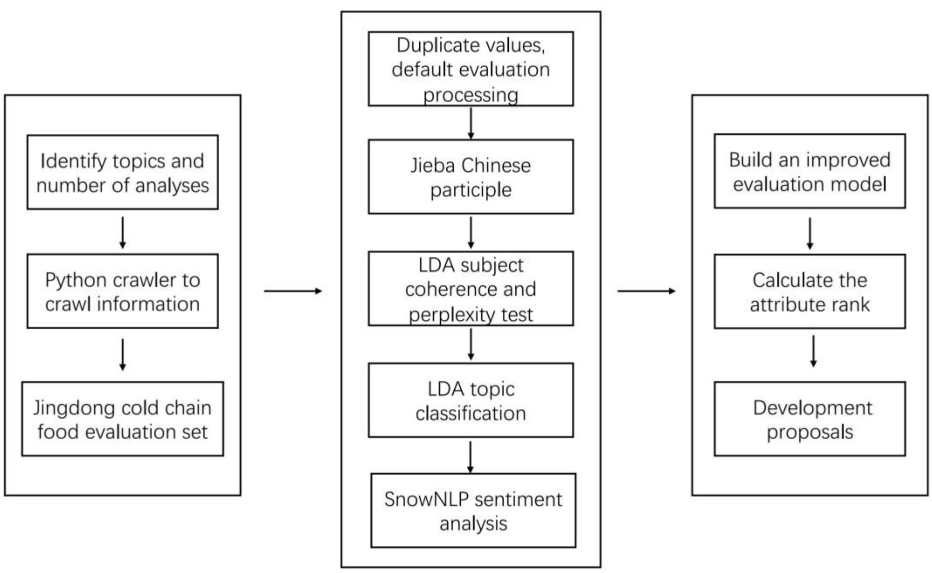

Figure 1. Research process

The first section is the collection of data. The study identifies cold chain food as the topic and selects six foods for the research. Writing code to automatically back crawl a web page for product comments by Python request and applying it to Jingdong's cold chain food products. In terms of results, 70,134 data were obtained, leaving 65,535 data after processing.

In the second section, the data was cleaned and subjected to word separation, then subjected to LDA topic analysis and sentiment analysis, respectively. In this case, the LDA topic model was written in Python and trained using the commentary training set. A coherence and perplexity analysis was conducted to determine the optimal number of topics to classify, and three topics were finally identified as optimal. In sentiment analysis using SnowNLP Sentiment Thesaurus, sentiment scores range from -10 to 10 and distinguish between negative, neutral, and positive attitudes using -3.3 versus 3.3 as a cut-off.

The third section is about Calculating the importance of product attributes and giving recommendations, using the negative comments distinguished in the previous step and combining them with the frequency of the keywords. Based on the results, the three themes were ranked in terms of importance food quality, prices, and logistics services. Lastly, suggesting improvements for e-commerce cold chain products.

2.4 Research Data

This paper crawls the cold chain food reviews of the famous Chinese e-commerce website Jingdong through Python request code. In terms of the classification of cold chain foods, they are generally divided into primary products and processed products, so this paper selects three more popular foods from each of the two types of products. The total number of reviews obtained is 70,134, and the number of reviews for each food is shown in the table.

Table 1. Number of reviews of cold chain foods

Cold chain food types	Food Name	Number of comments
Primary products	Avocado	13146
	Salmon	5405
	Fresh Chicken	4807
Processed products	Ice cream	13826
	Instant Frozen Dumplings	16022
	Cooked food	16928

3. Empirical Research Process and Results

3.1 Data Processing

For the research data obtained above this paper, after cleaning work such as removing duplicate values and abnormal comments, the remaining number of comments was 65535. The Jieba Chinese word separation tool was used to process them, and the attributes such as lexicality and frequency of each word in the comments were obtained, and the high-frequency words such as irrelevant words, brand names, and product names were excluded, as shown in the table.

Table 2. Top 30-word frequency words

Serial number	Glossary	Word Frequency	Serial number	Glossary	Word Frequency
1	Delicious	17190	16	Fresh	4590
2	Taste	14776	17	worthwhile	4445
3	Events	11550	18	Speed	4201
4	Packaging	8322	19	Brands	4185
5	Price	7995	20	Affordable	3916
6	Logistics	7464	21	Cheap	3629
7	Flavor	7456	22	Value for money	3348
8	Convenient	6137	23	Quality	3240
9	Courier	5756	24	Offers	3090
10	Quality	5578	25	Refrigerators	2577
11	Special	5574	26	Value for money	2454
12	Texture	5553	27	Self-employed	2306
13	Repurchase	5059	28	Trust	2176
14	Quick	4812	29	Delivery	2012
15	Satisfaction	4635	30	Flesh quality	1961

As can be seen from the table, consumers are mainly concerned about the quality, price, and logistics of food products.

3.2 LDA Theme Analysis

Using the results of the word separation process as a basis, a topic analysis model is constructed in Python. Before analyzing the topics, the coherence and perplexity of the data need to be calculated. In general, the higher the coherence the better, and the closer the perplexity to 1 the better, to get the appropriate number of topics.

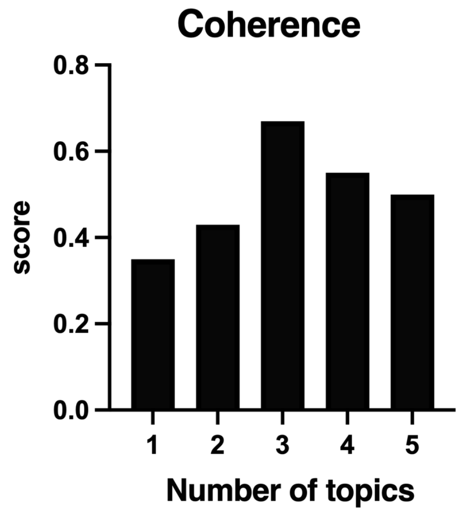

Figure 2. Coherence of LDA model

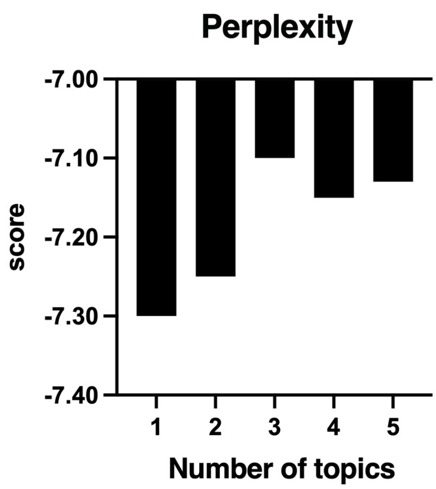

Figure 3. Perplexity of LDA model

From the above figure, the optimal number of comment coherence is 3, the optimal number of perplexity is 3, and the integrated optimal number is 3. Using this as the base number of topics, we bring in the data to obtain three corresponding topics and influencing factors and select the Top 10 of each topic for display.

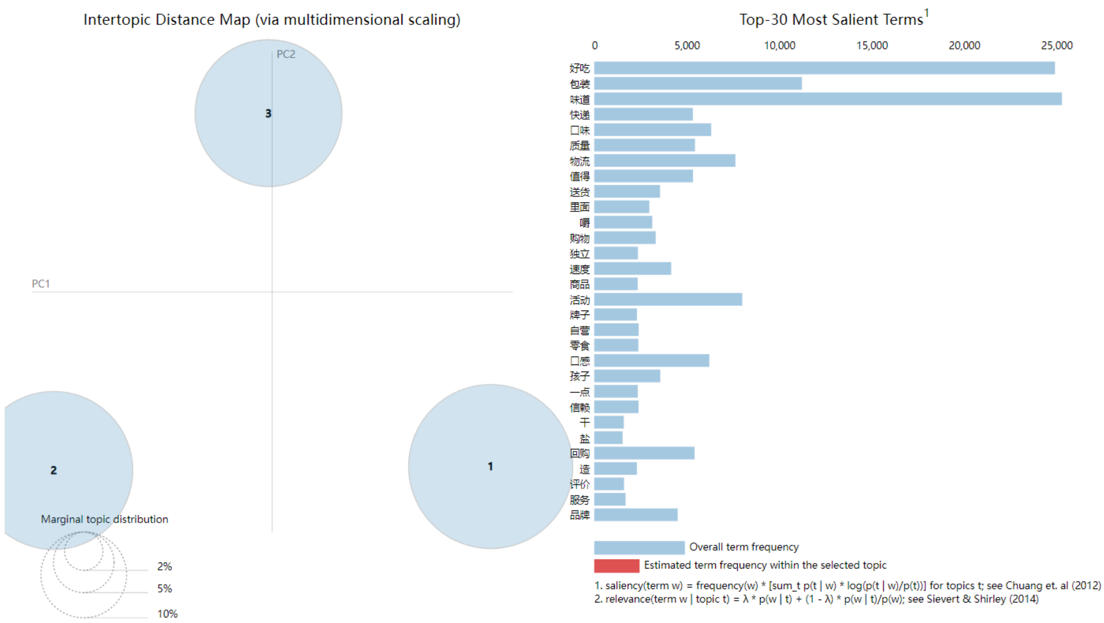

Figure 4. Results of LDA model

Table 3. Influencing factors of Topics

Comment Properties	Topics	Influencing factors
Cold Chain Food Review	Food quality	taste, delicious, flavor, repurchase, chewy, snack, air-dried, salty, hard, spicy
	Logistics Services	logistics, express, quality, speed, delivery, shopping, convenience, self-management, service, packaging
	Food Value for Money	worthwhile, price, value for money, quality, good value, affordable, events, convenience, kids, brands

As can be seen from the table and graph, the three themes are food quality, logistics services, and value for money of food. There is less correlation between the three themes, indicating that the thematic classification is effective. The main influence on food quality is the demand for taste and texture, which can be reflected in descriptions such as salt, spicy, hard, and dry, with high overall ratings, but the target group cannot adapt to certain flavors. Logistics services are mainly reflected in the attitude of delivery, the level of packaging, the degree of intactness, and convenience. Jingdong's own service level is relatively high in the same industry, with fast distribution speed, high standardization of packaging and in most cases well-preserved cold chain food. Food value for money is mainly reflected in price, activities, branding, and other aspects. Consumers are concerned about whether the purchase is affordable relative to physical shops and whether promotions are frequent, which is a major key to consumer satisfaction.

3.3 Sentiment Analysis and Importance Calculation

After the split word processing and topic analysis, sentiment analysis of the comments are required to derive a score for each topic and influencing factor, combined with word frequency to obtain the evaluation importance. In this paper, the sentiment analysis tool of SnowNLP is used, the default corpus is used as the basis for continuously updating the training, and the partial score ei results of the sentiment analysis are shown in the figure.

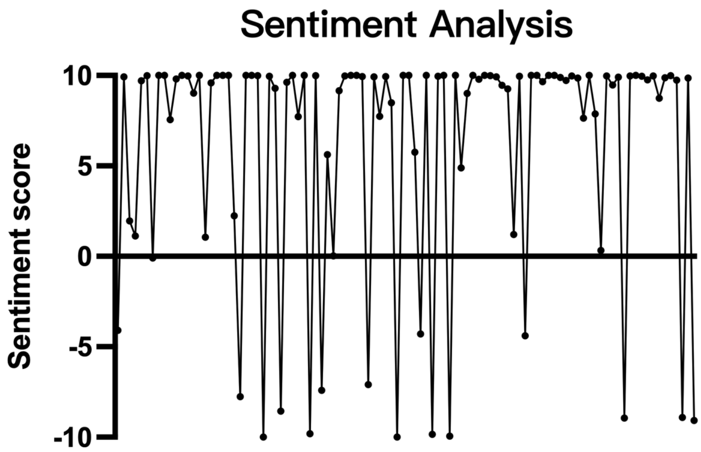

Figure 5. Sentiment score of 100 random cold chain food comments

Using 3.3 and -3.3 as criteria to distinguish between positive, negative, and neutral comments yields 44,565 positive comments, 10,167 negative comments, and 10,803 neutral comments, with a relatively high number of positive comments in line with the norm.

Table 4. Judgment criteria of comment

Type of comment	Judgment criteria	Number
Positive Comments	3.3 < ei ≤ 10	44565
Negative Comments	-10 ≤ ei < -3.3	10167
Neutral Comments	-3.3 ≤ ei ≤ 3.3	10803

Once the sentiment score for each comment is obtained, the data is sorted by topic to filter out the average sentiment score for the topic and the influencing factors. The lower the sentiment score, the higher the level of concern for the company, so the sentiment score is processed.

$$E_i = \left(\frac{1}{e_i - a} \right) f_i \tag{1}$$

Ei is importance, ei is sentiment score, fi is word frequency, a is a constant, and the average sentiment score is too concentrated and used to increase the differentiation between influences.

Table 5. Importance of topics and factors

Topics	Influencing factors	sentiment average score ei	Word frequency fi	Level of importance Ei	Theme importance
Food quality	Taste	4.8602	0.7522	12.4950	43.4356
	Delicious	4.8601	0.8751	14.5607	
	Texture	4.8676	0.3796	5.6154	
	Repurchase	4.8601	0.2575	4.2845	
	Chewing	4.8721	0.2412	3.3453	
	Snacks	4.8683	0.0248	0.3631	
	Air-drying	4.8679	0.0747	1.1001	
	Saltiness	4.8701	0.0592	0.8445	
	Hardness	4.8602	0.0389	0.6462	
	Spicy	4.8681	0.0123	0.1806	
Logistics Services	Logistics	4.8604	0.3800	6.2914	40.6125
	Express	4.8604	0.2930	4.8509	
	Quality	4.8601	0.2840	4.7255	
	Speed	4.8624	0.2139	3.4279	
	Delivery	4.8605	0.1987	3.2843	
	Shopping	4.8603	0.1572	2.6069	
	Save your mind	4.8604	0.3124	5.1722	
	Self-employed	4.8731	0.1174	1.6060	
	Services	4.8606	0.0969	1.5990	
	Packaging	4.8601	0.4236	7.0483	
Food Value for Money	Worthwhile	4.8602	0.2262	3.7574	42.0053
	Price	4.8601	0.4070	6.7720	
	Value for money	4.8602	0.1249	2.0748	
	Quality	4.8601	0.1649	2.7437	
	Value for money	4.8602	0.1704	2.8305	
	Affordable	4.8614	0.1993	3.2459	
	Events	4.8605	0.5880	9.7190	
	Convenient	4.8605	0.3124	5.1636	
	Kids	4.8601	0.1572	2.6156	
	Brands	4.8691	0.2130	3.0824	

Ranked by the importance scores in the table above, the Top 15 influencing factors that consumers value most for cold chain food are taste, delicious, activity, packaging, price, logistics, taste, saving, convenience, delivery, quality, repurchase, worthiness, speed, and chewiness. They are ranked in terms of the importance of the topic: food quality, food value for money, and logistics service. Moreover, the main reasons for dissatisfaction drawn from the comments regarding the impact factors were focused on the following areas.

(1) The taste and texture of the food itself are not in line with consumer preferences. To increase the storage time of the food, pickling and air-drying operations are carried out, resulting in the food will have a particular flavor. For example, the taste of cooked food such as pork knuckle is too heavy, dry, salty, and spicy, and the target consumer group is slightly narrower, affecting the sales of the food.

(2) The packaging is broken and crushed, damaging the fruit and vegetables. Furthermore, there is over-packaging and inconsistent packaging, indicating that the logistics scheduling is not done correctly. Consumers responded that one avocado in one package is inefficient to dismantle and causes a lot of waste, which is not in line with the concept of environmentally friendly consumption. Food damage is caused by ice cream and other food not being frozen with ice or melting ice during the delivery process.

(3) The products are less cost-effective. For example, salmon and avocado are more expensive compared to overseas, the portions are smaller, the delivery is slower, and they do not have an advantage compared to takeaway software purchases. At the same time, the purchase price of ice cream and salmon is higher compared to supermarkets and farmers' markets, resulting in an inversion of prices. In China, it is common knowledge that prices in online shops are lower than in physical shops, which is difficult for consumers to accept. The poor taste of chilled food arriving in transport is related to the temperature setting of the cold chain transport.

(4) In terms of marketing, consumers responded that the promotional pictures differed significantly from the real thing, and the promised weight was watery. After-sales service is poor compared to non-cold chain food, returns and refunds are slow, customer service is more perfunctory, and the overall shopping experience is not good.

3.4 Multiple Linear Regression Models and Validation

Multiple linear regression analysis was used, and the relationship between the three topics and the rate of poor product reviews was investigated. The first, second, and third principal component values were calculated, and the results are shown in the table.

Table 6. Multiple regression parameters

Number	First component value	Second component value	Third component value	Poor rating rate
1	45.23	39.51	43.22	0.057
2	40.92	42.72	37.14	0.021
3	43.12	40.56	42.44	0.042
4	42.32	36.43	38.67	0.012
5	45.15	44.78	45.73	0.092
6	41.86	41.48	44.89	0.067

Sampling 1/3 of the reviews as the validation set data, 2/3 as the training set data, and using the poor rating rate as the dependent variable, the data were subjected to multiple regression analysis using SPSSAU, and the equation was calculated as：

$$\mathrm{P}rr = -0.463 + 0.002 * Fcv + 0.004 * Scv + 0.006 * Tcv \quad (2)$$

Fcv is First component value, Scv is Second component value, Tcv is Third component value. Moreover, the model passed the F-test, $P = 0.025 < 0.05$.

The above multiple linear regression equation was tested using the remaining 1/3 of the sample and brought into the equation to give the difference between the predicted poor rating rate and the actual poor rating rate.

Table 7. Comparison between predicted poor rate and actual poor rate

Number	Predicted poor rate	Actual poor rate	Difference ratio
1	0.588	0.054	8.88%
2	0.022	0.023	-4.34%
3	0.041	0.037	10.81%
4	0.013	0.015	-13.33%
5	0.092	0.090	2.22%
6	0.058	0.064	-9.37%

It can be seen that the predicted and actual values of the poor rating rate for online reviews of cold chain food do not differ by a high percentage, with an average error of 8.15%. It shows that this evaluation system is somewhat accurate and further proves the validity of the model.

3.5 Development Proposals

Suggestions for product and service improvements for cold chain food products concerning the ranking of the importance of the influencing factors and the reasons for their occurrence.

(1) Strengthen market research to understand consumer taste preferences

Due to preservation needs or their taste positioning, many food products place too much emphasis on flavors such as spicy, salty, and dry textures, resulting in unacceptable to consumers and lowering the target consumer base. Feedback analysis of consumer reviews should be used to obtain preferences for individual product segments to further cater to consumers and expand market share.

(2) Improving packaging and distribution mechanisms and standards

For products such as fruit and vegetables that are delivered together in small quantities and in many types, a variety of standardized combination packaging should be designed to reduce waste and eliminate the phenomenon of one box of fruit. In the information system, packaging and order matching mechanisms should be added so that products with similar storage methods can be packaged and delivered together to increase efficiency. And conduct product traceability to ensure that problematic products can be traced to their source in the first instance, avoiding large-scale accidents due to food spoilage, reducing legal risks, and increasing consumer trust.

(3) Improve the after-sales service workflow

A uniform after-sales returns service is in place, and a minimum return time is set for different situations. Certain products in the cold chain should be prioritized for return service due to their short storage time and susceptibility to deterioration. And professional training for after-sales customer service, the efficiency of the service, attitude, and other consumer feedback as one of the criteria to determine the pay, from the system and behavioral regulation, to ensure the efficiency and quality of after-

sales service.

(4) Reducing overall cold chain transport costs

Promote the construction of cold chain logistics infrastructure, purchase, and layout of cold chain logistics equipment, develop new packaging and cold chain transport technology for different products, provide professional training for staff, improve the quality and efficiency of distribution, and ultimately reduce overall operating costs.

4. Conclusion

This paper summarises the shortcomings of the traditional questionnaire approach for cold chain food, which is inefficient and costly, based on sentiment analysis and LDA model topic classification analysis, providing some ideas for vendors to analyze the needs of online users shopping online. Through a custom Python program, 70,134 comments were initially obtained, and after removing duplicate values, default comments, and Jieba Chinese word separation, 65,535 valid comments were obtained. After LDA topic model analysis, three topics were distinguished: food quality, logistics service, and food cost-effectiveness. And after SnowNLP sentiment analysis, 44565 positive comments, 10167 negative comments, and 10803 neutral comments were distinguished. The analysis obtained the most important influencing factors of cold chain food to be concerned about are taste, delicious, activity, packaging, price, logistics, taste, saving, convenience, express, quality, repurchase, worth, speed, and chewing. Combining the causes of each influencing factor, the suggestions for improvement are put forward, giving cold chain food e-commerce manufacturers some basis for analysis and improvement.

The current study also has certain shortcomings. Firstly, the LDA theme model processing results are not stable enough, as there is a lack of thesaurus for cold chain food categories, so the disabled thesaurus is the result of a combination of manual addition and model training, which may lead to omission and over-deletion, resulting in some errors in the analysis results. Secondly, there is room for improvement in the amount of data collected, and it is expected that the overall amount can be increased in the future to improve the accuracy of topic analysis and sentiment analysis. Finally, there is a lack of specific implementation plans for product countermeasures, and it is hoped that the results of the improved model will be used as the basis for practical optimization plans in the future.

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Appendix A

Table of Nomenclature

Terminology	Explanation
LDA	Latent Dirichlet Allocation, generative probabilistic model of a corpus.
SnowNLP	A word splitting, sentiment analysis tool in Python.
Jieba	A Chinese word separation tool in Python.
Coherence	A metric for comparing different topic models based on human interpretability. The quality of the theme is measured by coherence.
Perplexity	A kind of index to evaluate the goodness of the language model, the smaller the perplexity, the better the sentence.
Python request	A Python-based HTTP library developed under the Apache2 Licensed License.