Exploring customer satisfaction in cold chain logistics using a text mining approach

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Abstract

Purpose-With the fierce competition in the cold chain logistics market, achieving and maintaining excellent customer satisfaction is the key to an enterprise's ability to stand out. This research aims to determine the factors that affect customer satisfaction in cold chain logistics, which helps cold chain logistics enterprises identify the main aspects of the problem. Further, the suggestions are provided for cold chain logistics enterprises to improve customer satisfaction.

Design/methodology/approach-This research uses the text mining approach, including topic modelling and sentiment analysis, to analyse the information implicit in customer-generated reviews. First, latent Dirichlet allocation (LDA) model is used to identify the topics that customers focus on. Furthermore, to explore the sentiment polarity of different topics, bi-directional long short-term memory (Bi-LSTM), a type of deep learning model, is adopted to quantify the sentiment score. Last, regression analysis is performed to identify the significant factors that affect positive, neutral and negative sentiment.

Findings-The results show that eight topics that customer focus are determined, namely, speed, price, cold chain transportation, package, quality, error handling, service staff and logistics information. Among them, speed, price, transportation and product quality significantly affect customer positive sentiment, and error handling and service staff are significant factors affecting customer neutral and negative sentiment, respectively.

Research limitations/implications-The data of the customer-generated reviews in this research are in Chinese. In the future, multi-lingual research can be conducted to obtain more comprehensive insights.

Originality/value-Prior studies on customer satisfaction in cold chain logistics predominantly used questionnaire method, and the disadvantage of which is that interviewees may fill out the questionnaire arbitrarily, which leads to inaccurate data. For this reason, it is more scientific to discover customer satisfaction from real behavioral data. In response, customer-generated reviews that reflect true emotions are used as the data source for this research.

Keywords: cold chain logistics, customer satisfaction, customer-generated review, text mining, topic modelling, sentiment analysis.

Paper type Research paper

1. Introduction

With the improvement of living standards, customers have increasingly higher demands on the quality of fresh products (Chen et al., 2019). The temperature is a key factor affecting the fresh product quality, that is, high temperature aggravates product spoilage (Liu et al., 2020a). In this context, cold chain logistics, due to the characteristics of ensuring product quality through low temperature, has become the main circulation method of fresh products (Li et al., 2019). In addition to temperature, the increasing time will reduce the fresh products quality (Wang et al., 2017). Therefore, compared with ordinary logistics, cold chain logistics has higher requirements, which has brought huge challenges in the customer service field to cold chain logistics enterprises. Nowadays, the price advantage is no longer obvious for enterprises, and they strive to find new competitive advantages to improve customer satisfaction. Only in this way can they cultivate loyal users to stand out from competition in the cold chain logistics market (Wang et al., 2020). Therefore, how to improve logistics services to increase customer satisfaction is worthy of in-depth exploration by cold chain logistics enterprises (Dai et al., 2020).

Customer satisfaction measurement is the key to understanding the current service level of cold chain logistics enterprises, which can strengthen the communication between customers and enterprises (Ferrentino and Boniello, 2020). Moreover, the key factors affecting customer satisfaction can be identified through measurement, which is conducive to discovering the cold chain logistics enterprise's advantage and disadvantage, thereby improving the logistics operations (de Aquino et al., 2019). However, most of the research on cold chain logistics at this stage focuses on the operations (distribution management and inventory management), and the research on customer satisfaction measurement is limited. In the limited research, data comes from questionnaires, which causes incomplete understanding. In response, the customer-generated reviews that has appeared in recent years allow customer satisfaction to be better interpreted (Zhu et al., 2020). Compared with questionnaires, customer-generated reviews are self-generated by the customer, which can better reveal the customer's attitude and evaluation of the cold chain logistics service process (Lucini et al., 2020). In addition, it can promote cold chain logistics enterprises to understand the true needs of customers to provide customers with high-quality services. In this context, how to efficiently perform text mining on a large number of customer-generated reviews has become the focus of the research field (Liang et al., 2020).

Two text mining approaches, topic modelling and sentiment analysis, are used in this research. Topic modelling is very prominent in displaying discrete data, and can provide an effective method for discovering hidden meanings in massive amounts of information (Jelodar et al., 2019). Therefore, topic modelling technology can identify the topics that customer-generated reviews focus on, which lays the foundation for the next step of sentiment analysis. Regarding sentiment analysis, most of the research on customer-generated reviews is coarse grained, that is, judging the sentiment polarity of the entire review. However, such a method is not comprehensive because various aspects are often involved in reviews (Do et al., 2019). For example, determine the sentiment polarity of "The delivery speed is fast, but the service attitude is very poor." In this review, if the analysis aspect is the logistics service speed, the polarity is positive, but it is negative when considering the service quality. This result shows that the sentiment polarity is opposite when considering various aspects (Shuang et al., 2019). Therefore, performing aspect-level sentiment analysis is an important research topic and is considered a fine-grained task that can provide more in-depth result analysis.

Overall, this research attempts to analyse customer-generated reviews using a text mining approach (topic modelling and sentiment analysis) to determine the fine-grained sentiment of customers and further provides guidance for cold chain logistics enterprises to improve customer satisfaction. Three contents are included in this research. First, a latent Dirichlet allocation (LDA) model is used to identify topics that affect customer satisfaction in cold chain logistics. Second, the bi-directional long short-term memory (Bi-LSTM) model is used to calculate the sentiment score of the topics involved in the customer generated reviews, and customer sentiment is determined according to the total score, including positive, neutral and negative. Finally, the significant influencing factors of sentiment are determined through the regression analysis of sentiment score (independent variables) and customer sentiment (dependent variables). Through the above research content, the voice of customers can be heard. This research has contributed to academia and industry. In academia, this research is an earlier research using a text mining approach to explore cold chain logistics customer satisfaction, which bridges the knowledge gap and promotes the cross-integration of different fields. In the industry domain, this research helps cold chain logistics enterprises find the influencing factors that affect customer sentiment and provides feasible suggestions to improve customer satisfaction.

The structure of this research is as follows. Section 2 conducts a literature review of logistics customer satisfaction and sentiment analysis. The research methods are proposed in Section 3. Section 4 introduces the case study. Section 5 analyses the results, which is consisted of topic modelling, sentiment analysis and regression analysis. The discussion is presented in Section 6. Finally, Sections 7 outlines the theoretical contributions, managerial implications and limitations.

2. Literature review

2. 1 Customer satisfaction in cold chain logistics

Usually the relationship between logistics customer satisfaction and measurement topics is nonlinear, so it is a challenging task to evaluate logistics customer satisfaction (Tontini et al., 2017). In recent years, many studies have explored customer satisfaction in the logistics field, which involves many industries, including online shopping, manufacturing, pharmaceuticals and ports (Abdullah et al., 2020; Chen et al., 2020; Choi et al., 2019; Duc Nha et al., 2020). It is worth noting that the research on customer satisfaction in the field of cold chain logistics is still very limited (Kilibarda et al., 2020). In the limited studies, most of them are combined with the vehicle routing problem (Qin et al., 2019; Song et al., 2020a; Wang et al., 2017; Wang et al., 2020; Zhao et al., 2020). In these studies, customer satisfaction is reflected through the punctuality of delivery. For example, Qin et al. (2019) proposes a comprehensive cold chain vehicle routing problem optimization model with the objective function of minimizing the cost of a unit satisfied customer. In their research, customer satisfaction is measured through the delivery time. However, in addition to delivery time, customer satisfaction is also affected by many factors. Tontini et al. (2017) notes that the factors such as safety, reliability, speed, helpfulness, communication, flexibility and fault recovery all have an impact on customer satisfaction. Therefore, research on combining cold chain logistics with vehicle routing problems to explore customer satisfaction is incomplete.

In response, more comprehensive research was carried out by Zhang et al. (2020), who adopt the catastrophe progression method to evaluate the service quality of cold chain logistics from five dimensions: reliability, responsiveness, accessibility, economy and flexibility. However, their research is an empirical study, and the data come from questionnaire surveys, which leads to the collected data having the following shortcomings. First, not all interviewees can fill out the questionnaire carefully, and filling in randomly will lead to untrue data (Lucini et al., 2020). Second, the dimensions of the questionnaire were generated based on the previous research results, which cannot promote the generation of new factors (Guo et al., 2017). In addition, problems cannot be discovered in time through questionnaires, which is not conducive to timely changes. In view of the shortcomings of questionnaires, some scholars have proposed using customer-generated reviews as a channel to obtain information in the field of customer satisfaction research (Ibrahim and Wang, 2019; Nie et al., 2020; Tsai et al., 2020).

With the development of Internet technology, an increasing number of consumers choose to comment on services, which provides a strong guarantee for obtaining true information (Guo et al., 2017). Compared with questionnaires, customer-generated reviews are more helpful to managers because these reviews reflect customers' true feelings (Heng et al., 2018). At present, most of the research on customer-generated reviews focuses on hotel accommodation, online shopping, social media and tourism (Heng et al., 2018; Nie et al., 2020; Xiang et al., 2017). To our knowledge, only one study has focused on cold chain logistics. Specifically, Hong et al. (2019) used a text mining approach to analyse customer-generated reviews to obtain the significant factors affecting customer satisfaction in fresh e-commerce logistics services, and the results showed that convenience, communication, reliability, and responsiveness had a significant impact on customer satisfaction. In their research, customer satisfaction was the dependent variable during the process of correlation analysis, including positive and negative evaluations. However, in reality, in addition to positive and negative evaluations, there are also some neutral evaluations. Therefore, this research further refines the sentiment polarity, and it is divided into positive, neutral and negative, which indicates that three disordered dependent variables (positive, neutral and negative) are included. Regression analysis of disordered dependent variables is a challenge, and this research uses multivariate logistics regression analysis to achieve this process (Wu and Chang, 2020). Based on the above analysis, this research attempts to determine the factors that affect customers' positive, neutral and negative emotions by mining customer-generated reviews in cold chain logistics.

2. 2 Text mining approach

2.2.1 Topic modelling

In the face of chaotic text content, topic modelling can discover hidden topics to help understand, classify and summarize the text content (Kirilenko et al., 2021). Traditionally, the topic modelling of texts is based on manual methods, but as the text content increases, the traditional manual method is no longer suitable (Hagen, 2018). With the development of information technology, computer-aided topic analysis methods that can discover topics by analysing words that appear in text content have shown good prospects (Jelodar et al., 2019). In response, Blei et al. (2003) proposed using LDA to identify the hidden topics in the text, which is an unsupervised method. Its core idea is that when a document is created, each word has been extracted from the topic word set with a certain probability, and the topic is extracted from the topic set with a certain probability (Liang et al., 2020). Since then, LDA technology has aroused widespread attention and researchers have begun to use LDA to explore a representative set of topics in text content (Jelodar et al., 2019; Maier et al., 2018; Zhang et al., 2021). These studies show that LDA can extract topics from text without any inducement. To date, LDA has become the most widely used topic modelling method (Mutanga and Abayomi, 2020).

At present, much research on LDA is carried out in academic and industrial circles. (Bu et al., 2021; Liu et al., 2019; Lucini et al., 2020; Sutherland and Kiatkawsin, 2020). However, specific research on the application of LDA to the field of customer satisfaction is still limited. After analysing the existing literature, it is found that most of the research focuses on tourism (Kirilenko et al., 2021; Taecharungroj and Mathayomchan, 2019), accommodation (Guo et al., 2017; Nie et al., 2020) and online shopping (Wu and Chang, 2020). The reason for this result may be the rapid development of online review sites in these industries. In these studies, LDA is used to identify the topics that customers focus on. For example, Wu and Chang (2020) used LDA to identify seven topics that affect customer sentiment polarity in online shopping, including payment, price, retailer return/refund, communication, product, delivery and promotion. However, to our knowledge, there is still no research using LDA to determine the topics in customer-generated reviews in the logistics field, let alone cold chain logistics. Therefore, to bridge this research gap, this research adopts the LDA model to mine the hidden topics in customer-generated reviews that affect customer satisfaction in the cold chain logistics field.

2.2.2 Sentiment analysis

Sentiment analysis, also known as opinion mining, is an important research direction in the field of text mining approaches, and it can detect the opinions and emotions (positive, neutral and negative) expressed in customer-generated reviews (Lucini et al., 2020). At present, there are some studies that apply different sentiment analysis approaches to analyse customer-generated reviews in various industries, such as hotels, online shopping, social media and tourism (Heng et al., 2018; Ibrahim and Wang, 2019; Zhu et al., 2020). Through the analysis of existing research, sentiment analysis approaches can be divided into three categories: dictionary-based, machine learning and deep learning (Liang et al., 2020; Liu et al., 2020b; Wu and Chang, 2020).

The principle of the dictionary-based approach is to match the sentiment words in the reviews with those in the dictionary (including positive and negative), and further combine the negative words and degree adverbs in the reviews to calculate the sentiment score; finally, the sentiment polarity is determined (Singh and Gupta, 2019). For example, Wu and Chang (2020) used a dictionary-based approach to identify the sentiment polarity of online shoppers' posts. However, the accuracy of this approach depends on the quality of the constructed sentiment dictionary, which highlights the existence of the following flaws (Bernabe-Moreno et al., 2020). At present, there is no general dictionary for the logistics field, and the establishment of the dictionary requires considerable manpower and material resources. Moreover, Zhu et al. (2020) stated that in the Internet age, new words are emerging one after another, and the meanings of words are constantly changing, which makes it very difficult to maintain the dictionary.

Compared with the dictionary-based approach, the machine learning approach shows better performance (Ghiassi and Lee, 2018). It can be divided into three categories: supervised, semi-supervised and unsupervised approaches. Among them, the most mainstream approach is supervised machine learning due to the accuracy of its result (Martin-Valdivia et al., 2013). In the field of sentiment analysis, machine learning transforms it into a classification problem, which is classified according to the set sentiment including positive, neutral, and negative (Basiri et al., 2020). The process is generally to extract emotional features in the text, construct a classification model, train the model through sample data, and finally use the model to predict the emotional classification of other texts (Ghiassi and Lee, 2018). However, machine learning also has some problems that need to be overcome. Nie et al. (2020) noted that machine learning needs to select different emotional features according to different data sets, which leads to poor generalization ability of the model because models in various fields cannot be mutually used. In addition, in the machine learning approach, emotional characteristics are reflected in individual words, but in fact, the context of words also has an important influence on the meaning of words, which affects the quality of classification (Wu et al., 2019).

Given the problem of machine learning, deep learning has recently become a prospective type of machine learning in sentiment analysis. It does not need to select emotional features, which reduces the degree of reliance on humans (Araque et al., 2017). At the same time, it also considers the semantic relationship of the context so that the classification effect is improved (Pasupa and Ayutthaya, 2019). Deep learning is a hierarchical feature learning model; first, the data need to be transformed into word vectors through text representation methods, and then the emotional information in the text is learned by building a deep neural network model (Colon-Ruiz and Segura-Bedmar, 2020). Currently, there are two mainstream models of deep learning in sentiment analysis, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs) (Behera et al., 2021). Compared with CNNs, RNNs can better preserve sequence information and prevent loss. However, RNNs have the problems of gradient disappearance and explosion (Li et al., 2020). To overcome the shortcomings of RNNs, long short-term memory (LSTM) has been proposed (Liang et al., 2020). Of course, the traditional LSTM also has the problem that it can only learn the above information of the text but cannot learn the following information, which results in inaccuracy in expressing the sentiment in the text (Jain et al., 2020). In response, this research proposes to use bi-directional long short-term memory (Bi-LSTM) for sentiment analysis, which can perform bi-directional learning to obtain more comprehensive information. As far as we know, this is the first research that uses the BI-LSTM method to explore customer satisfaction in cold chain logistics.

Based on the above analysis, the innovations of this research are embodied in the following aspects. First of all, this research proposes to use customer-generated reviews as the source of research data, which ensures the information accuracy. Secondly, the LDA and Bi-LSTM are used to extract the information of customer-generated reviews, which provides data for finding out the significant influencing factors of customer satisfaction. Lastly, this research uses a disordered multi-category logistic regression model to determine the significant factors that affect customers' positive, neutral, and negative emotions.

3. Proposed methodology

Figure I shows the four-step methodology framework proposed in this research. The first step is data collection and pre-processing, and topic modelling is carried out through the LDA model in the second step to identify the topics that customer focus on. The third step use Bi-LSTM to score the topics covered in each customer-generated review, and further determine the sentiment polarity of the reviews. Finally, regression analysis is performed to identify the significant factors that affect sentiment polarity (negative, neutral, and positive) based on the topic score and review sentiment polarity. The method proposed in this research is described in detail below, and the key variables of the proposed methods are listed in Table A1.

3.1 Data pre-processing

Since customer-generated reviews usually contain irrelevant data, it is necessary to pre-process the collected reviews to prevent irrelevant data from affecting the accuracy of the results. The data pre-processing consists of three stages. The first stage is data cleaning (Liang et al., 2020). The expression of the reviews is close to everyday language, usually containing various pictures and symbols. Therefore, it is necessary to process the noise data and only keep the text. The regular expression method of Python is adopted to clean the data. The second step is word segmentation (Wu and Chang, 2020). The expressions in Chinese and English are different. In English, one word usually represents a noun or adjective, and the words are separated by spaces. However, a single word cannot express its meaning in the Chinese expression. Therefore, word segmentation of Chinese text is a very important operation. This research uses a Chinese text segmentation toolkit, Jieba, to perform this step. To further improve the usefulness of text information, the third stage needs to remove stop words, such as modal particles, structural auxiliary words and conjunctions (Liu et al., 2020b).

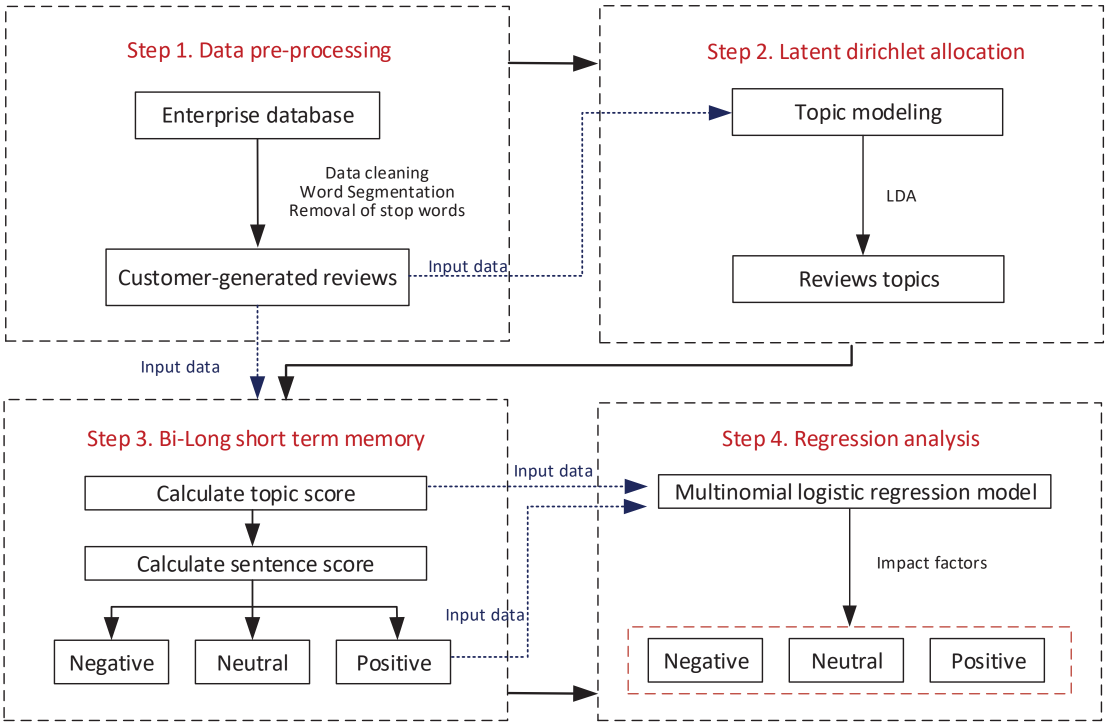

Figure I. Framework of proposed four-step methodology.

3.2 Latent Dirichlet allocation (LDA)

LDA is a three-layer Bayesian model that contains documents, topics and words, and it describes the relationship among documents, topics and words (Guo et al., 2017). The LDA model is shown in Figure II, in which M, N, K represent the total number of documents, words and topics, respectively, w represents the world, z represents the topic to which a word belongs, θ represents the probability distribution of the document-topic, ϕ represents the probability distribution of the topic-word, and α, β represent the hyperparameters of θ and ϕ, respectively.

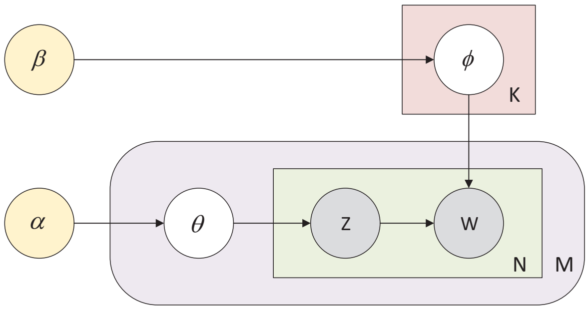

Figure II. Model of LDA.

The occurrence probability of the $i\text{-}th$ word in the document is calculated as formula (1), in which $P(w_i|z_i = k)$ represents the probability of word w_i belonging to topic k and $P(z_i = k|m)$ represents the probability of topic k belonging to document m.

$$P(w_i|m) = \sum_{k=1}^{K} P(w_i|z_i = k)\, P(z_i = k|m) \tag{1}$$

The solution of the LDA model is to solve the two parameters in formula (1), $P(w_i|z_i = k)$ and $P(z_i = k|m)$. The Gibbs sampling method is usually used to approximate the above two parameters (Liang et al., 2020). The algorithm process is as follows:

Step 1: Set the appropriate total number of topics K and the parameters α and β.

Step 2: Each word w in the document is randomly assigned a topic z.

Step 3: Estimate the conditional probability of the word belonging to the topic according to formula (2), in which $\rightarrow i$ represents not including the $i\text{-}th$ term, $n_k^{w_i}$ represents the number of occurrences of word w_i in topic k, n_m^k represents the number of occurrences of topic k in document m, and β_w, α_k represent the Dirichlet of the word and topic, respectively.

$$P(z_i = k|\overrightarrow{z_{\rightarrow i}}, \vec{w}) \propto \frac{n_{k,\rightarrow i}^{w_i} + \beta_w}{\sum_{w=1}^{N} n_{k,\rightarrow i}^{w_i} + \beta_w} \left(n_{k,\rightarrow i}^{w_i} + \alpha_k\right) \tag{2}$$

Step 4: A new topic is randomly selected for word w_i according to the probability of word w_i belonging to topic z. Continue to randomly select the topic of the next word until the parameters θ and ϕ converge, stop the operation, and calculate the value of θ and ϕ

according to formulas (3) and (4).

$$P(w_i|z_i = k) = \phi_{k,w} = \frac{n_k^{w_i}+\beta_w}{\sum_{w=1}^{N} n_k^{w_i}+\beta_w} \tag{3}$$

$$P(z_i = k|m) = \theta_{m,k} = \frac{n_m^k+\alpha_k}{\sum_{k=1}^{K} n_m^k+\alpha_k} \tag{4}$$

3.3 Bi-directional long short-term memory (Bi-LSTM)

Bi-LSTM is composed of forward LSTM and reverse LSTM, and Figure III shows its structure, in which tanh represents the hyperbolic tangent function, δ represents the sigmoid function, x_t is the current input, and h_{t-1} is the output of the hidden layer at the last moment. In each LSTM module, there are three gates: forget gate f_t, input gate i_t, output gate o_t, and a memory unit c_t. The operation steps are as follows. In the following formulas, W_f, W_i, and W_o represent the weight matrices of the forget, input and output gates, respectively, and b_f, b_i, and b_o are the biases of the forget, input and output gates, respectively.

Step 1: According to formula (5), determine the lost information through the forget gate, and output a value between 0 and 1 for each number in cell C_{t-1}, where 1 means completely reserved and 0 means completely discarded.

$$f_t = \delta\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{5}$$

Step 2: Determine the new information stored in the cell state, and this stage includes two parts. First, the information is updated through the input gate according to formula (6), and then the tanh layer creates a new candidate value vector according to formula (7).

$$i_t = \delta(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{6}$$

$$c_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{7}$$

Step 3: Update the old cell state and output the new cell state according to formula (8).

$$C_t = f_t \cdot C_{t-1} + i_t \cdot c_t \tag{8}$$

Step 4: Determine the output value $\mathrm{h_t}$. Run the sigmoid layer to determine the output cell state, as shown in formula (9), further process the obtained cell state through tanh (obtain a value between -1 and 1), and finally multiply the above two results according to formula (10).

$$o_t = \delta(W_o \cdot [h_{t-1}, x_t] + b_0) \tag{9}$$

$$h_t = o_t \cdot tanh(C_t) \tag{10}$$

Step 5: In Bi-LSTM, there are two time steps of one forward and one reverse at any time, and their states are shown in formulas (11) and (12), respectively.

$$\overrightarrow{h_t} = LSTM\left(x_t, \overrightarrow{h_{t-1}}\ \right) \tag{11}$$

$$\overleftarrow{h_t} = LSTM\left(x_t, \overleftarrow{h_{t-1}}\ \right) \tag{12}$$

Step 6: Combine the output h_t (forward) and h_t (reverse) of the last time step of the model to obtain h_n, which ensures that the features of the text can be more comprehensively represented. Use a fully connected network to process h_n, which reduces the dimension of h_n to the same dimension as the category. The formula is formula (13), where w_t, b_t represents the weight matrix and bias of the fully connected network, respectively.

$$X_t = W_t\left[\overrightarrow{h_t}: \overleftarrow{h_t}\right] + b_t \tag{13}$$

Step 7: Use the sigmoid function (formula (14)) to convert the value of X_t to a number between 0 and 1. Next, binary cross entropy is applied to the current multi-label classification, which calculates the difference (BCE) between the current output result δ and the true value y_i at the position of each label, as shown in formula (15), where $i \in [1, C]$ and C represents the total labels. Finally, the BCE value should be averaged according to formula (16), and the lower the BCE value is , the better the effect of the model.

$$\delta = \frac{1}{1+e^{-x}} \tag{14}$$

$$BCE(i) = -[y_i \, log\, \delta + (1 - y_i)\, log(1 - \delta)] \tag{15}$$

$$BCE = \textstyle\sum_i^C BCE(i)/C \tag{16}$$

Step 8: Use gradient descent to reverse the new parameters to complete the model training.

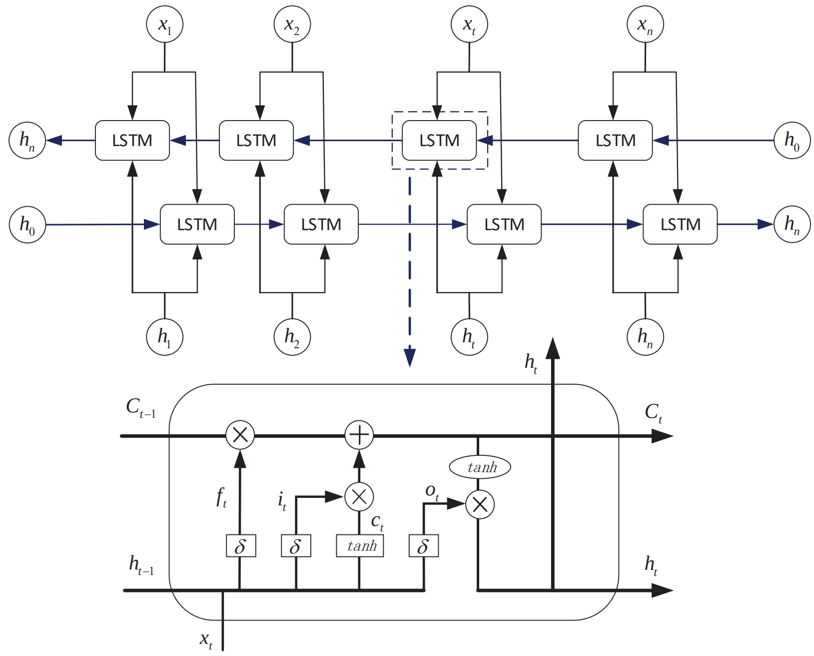

Figure III. Structure of Bi-LSTM.

3.4 Regression analysis

The dependent variables in this research include positive sentiment, neutral sentiment and negative sentiment. Therefore, the multivariate logistics regression model is established, as shown in formula (17).

$$ln\left[\frac{p(y=j|x)}{p(y=J|x)}\right] = \alpha_j + \sum_{k=1}^{K} \beta_{jk}\, x_k \tag{17}$$

In this model, j represents the dependent variables, and the value of $j = 1, 2, 3$, where 1,2 and 3 represent the negative, neutral and positive sentiments, respectively. J represents the reference category of sentiment, x_k represents the k- th independent variable that affects the sentiment polarity, β_{jk} represents the regression coefficient of the independent variable, and $p(y=j|x)/p(y=J|x)$ represents the probability ratio of sentiment polarity j to J. This research uses negative sentiment as a reference, and the logistics model is established as formulas (18) and (19).

$$ln\left[\frac{p2}{p1}\right] = \alpha_1 + \sum_{k=1}^{K} \beta_{1k}\, x_k \tag{18}$$

$$ln\left[\frac{p3}{p1}\right] = \alpha_3 + \sum_{k=1}^{K} \beta_{3k}\, x_k \tag{19}$$

4. Case study

4.1 Case implementation

Enterprise A (for the sake of anonymity, referred to as Enterprise A) is a leading cold chain logistics enterprise in the Southwest of China, that provides customers with various cold chain services such as urban distribution, long-distance transportation, and cold storage warehousing. Enterprise A is well equipped with cold chain resources, and has more than 200 refrigerated trucks for urban distribution. In addition, it pays attention to the construction of information system, and has established a customer management system. The customer can evaluate the logistics service in the management information system after receiving the service, which is conducive to timely discovery of the problems in the logistics process.

According to the method framework proposed in Section 3, this research conducted a customer satisfaction survey of Enterprise A. First of all, this research collected 3702 customer-generated reviews between May 2020 and July 2020, and the customer-generated reviews come from small- and medium-sized supermarkets served. In the end, 3512 valid customer-generated reviews are obtained after data processing. Secondly, topic modeling was performed on the customer-generated reviews obtained in the first step to determine the topics that customers pay attention to. Thirdly, each topic was scored in each customer-generated review, and the total score of the review was obtained. Finally, a regression analysis was performed based on the scores in the third step, and the significant influencing factors of positive, neutral and negative sentiments were found.

4.2 Parameter setting

Combing the research of Liang et al. (2020) and Gao et al. (2019), as well as the research experience, the experimental parameters are set as follows: (1) The values of α and β in the LDA model are both 0.01. (2) The time step of LSTM is 128. The excess part is deleted when the sentence length exceeds 128, and it will be supplemented with zero if the sentence is less than 128. The early stopping mechanism is set. The training ends after 5 epochs (data training round) when the accuracy of the results on the verification set is not increased, which can prevent overfitting. The batch number (the number of sentences per training) is set to 64, the learning rate is 2e-3, and the random number seed is set to 42. The Adam optimizer is used to update the gradient descent direction. The experimental environment is a graphics card RTX2080Ti with 11G video memory, using Pytorch 1.2 version. This research uses 60% of the data as the training set, 20% for the validation set, and 20% for the test set.

5. Results and Analysis

5.1 Topic modelling

In previous studies (Liu et al., 2020b; Lucini et al., 2020), perplexity was used to determine the optimal number of topics in the LDA model. The perplexity decreases as the number of topics increases. A lower perplexity means that a better classification effect, but too many topics make it difficult to explain its meaning. Therefore, a balance should be achieved between perplexity and interpretability. In this research, the result of perplexity is shown in Figure IV. The perplexity value drops sharply when the number of topics increases to eight, and the perplexity value drops slightly when the number of topics exceeds eight. Therefore, the optimal number of topics in this research is set to eight (Wu and Chang, 2020). Next, the LDA model is carried out to identify the key word in each topic, and Table I lists the top ten probability factors for each topic. The naming of each topic is carried out independently by the first and second authors of this research, and then opinions are exchanged. If there was disagreement, the third author was consulted for discussion, and eight topics were finally chosen, namely, speed, price, cold chain transportation, package, quality, error handling, service staff and information.

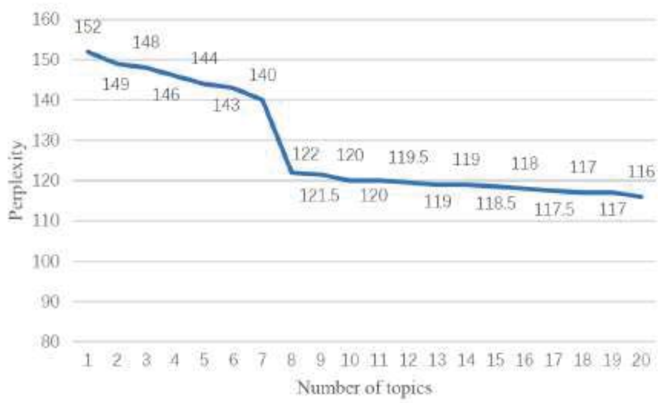

Figure IV. Perplexity under different topics.

To evaluate the effectiveness of topic modelling, this research adopts the method proposed by Hagen (2018). The first step is human interpretability, which specifically refers to two experts in the field evaluating whether a set of keywords can be assigned to the same topic. As a result, seven groups are rated as having good quality topics, and one group is rated as an intermediate quality topic. The agreement score between two experts is 0.85, indicating that they have good reliability. The second step is computer-human interrater reliability, which refers to an expert randomly extracting text content, and classifying it into a certain topic, further comparing the results with the classification of the LDA model. Finally, the Kappa coefficient of computers and humans is 0.84, which shows that there is good agreement between humans and computers. The third step is to compare with the factors found in existing research. Hong et al. (2019) discussed five factors that affect customer satisfaction in fresh e-commerce logistics services, namely, convenience (whether it is convenient to receive goods), communication (attitude of service and delivery staff), integrity (package), responsiveness (speed of logistics distribution) and reliability (consistent with the description on the webpage). The topics found in this research overlap with their findings, such as the speed of logistics, package, and service staff, but there are differences. Specifically, the object of their research is ordinary consumers, while the object of this research is the company, so the influencing factors are different. In summary, the evaluation results of the LDA model are acceptable.

Table I. Results of topic modelling.

Topic1: Speed	Topic2: Price	Topic3: Cold chain transportation	Topic4: Package
Logistics	Price	Low temperature	Solid
Fast	Expensive	Freezing	Foam
Speed	Cheap	Vehicle	Ice bag
Arrival	Cost	Entire journal	Careful
Delivery	Moderate	Transport	Seal
Qualified	Shipping	Temperature	Broken
Slow	Market	Control	Fine
Ship	Reasonable	Freezer	Worn
Rapid	Cost-expensive	Room temperature	Very bad
Not good	Traffic	Tool	Plastic
Topic5: Quality	Topic6: Error handling	Topic7: Service staff	Topic8: Information
Fresh	Feedback	Attitude	Location
Hard	Not enough	Customer service	Inquiry

Taste	Error	Qualified worker	Search
Measures	Reply	Enthusiasm	Information
Quality	Return	Deliver the goods	Position
Vegetables	Contact	Disgusting	Where
Flavour	Response	Telephone	Manner
Spoilage	Timely	Problem	Track
Retail	Lose money	Profession	Place
Save	Replenishment	Intimate	Update

5.2 Sentiment analysis

This research is fine-grained sentiment research on customer-generated reviews, including aspect identification and sentiment scoring, which makes it more challenging than either aspect identification or emotional scoring alone. The aspect identification is based on the topics determined by the LDA model in Section 5.1. Regarding sentiment scoring, this research sets the scoring rules shown for the eight topics extracted to quantify the level of logistics services, thereby determining the final sentiment polarity, including positive, neutral and negative. However, it is worth noting that Table II does not cover all the key words scored, only the most frequent ones. At present, most evaluation websites adopt a five-point system. This research also adopted such a setting, with 3 as neutral, greater than 3 as positive, and less than 3 as negative. The score is 3 when the topic is not mentioned in the review; that is, the topic is considered to be neutral. According to this rule, if the score of a review is greater than 24, the review is classified as positive sentiment, and if the total score is less than 24, the sentiment polarity is recorded as negative. The review is judged to be neutral when the score is equal to 24.

Table II. The scoring criteria of eight topics.

Topics	5 score	4 score	3 score	2 score	1 score
Speed	Rapid/Fast	Quickly	General	Slow	Very slow
Price	Cheap	Cost-effective	Reasonable	Expensive	Too expensive
Cold chain transportation	Whole cold chain	Cold chain	Freezer	Not cold chain	Room temperature
Package	Solid	Careful	No damage	Not good	Damage
Quality	Very fresh	Fresh	Stable	Not fresh	Spoilage
Error handling	Well	Timely	Normal	Not deal with	Very bad
Service staff	Enthusiasm	Good attitude	General	Bad attitude	Very bad

Information	Very good	Timely update	Query location	Not update	Useless

Note: All words are translated from Chinese.

Before inputting the data into the Bi-LSTM model, it is necessary to label the data and transform the text vector. The first is data labelling. In this research, there are eight topic labels, and there are five score labels under each topic. Therefore, a total of forty sentiment labels are formed, as shown in Table A2 in the Appendix. Furthermore, the labeling formula: E=5T+S is obtained through Table AI. For example, a particular review is labelled as follows. "The logistics are fast, the package is solid, the product is fresh, and the staff show enthusiasm.” The final result is “Speed: 5*0+4=4”; similarly, “Package: 19, Quality: 23, and Service staff: 34”, so the label of the review is (4, 19, 23, 34). However, the Bi-LSTM model can only recognize the 0-1 form, so the label (4, 19, 23, 34) needs to be converted to 0-1, that is, the label involved in each review is labelled in 40 sentiment labels, so the label [0，0，0，0，1，0，0，0，0，0，0，0，0，0，0，0，0，0，0，1，0，0，0，1，0，0，0，0，0，0，0，0，0，0，1，0，0，0，0，0] is formed. The second is text vector conversion. The input embedding layer maps the original text representation to a high-dimensional vector space, and word2vec is used to obtain the embedding representation of each word in this research. Finally, the scores of the reviews are obtained, and Table III shows the scores of some reviews. After statistical analysis, 3512 scored reviews were obtained, including 3191 positive sentiment reviews, 213 neutral reviews and 108 negative reviews. Judging from the results, the enterprise's favourable rate is much higher than the negative rate.

Table III. Score of some customer-generated reviews.

N	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic6	Topic7	Topic 8	Score	Sentiment
1	5	3	3	5	4	3	5	3	31	Positive
102	4	5	3	2	5	3	3	4	29	Positive
145	4	3	4	2	3	3	2	3	24	Neutral
201	3	3	3	3	3	3	3	3	24	Neutral
245	5	2	3	2	3	2	2	3	22	Negative
301	2	3	2	3	3	3	2	3	21	Negative

In the test set, the RNN, LSTM and Bi-LSTM models are used to calculate the sentiment score to determine the effect of the model, and the precision rate (P), recall rate (R) and F1 value are the evaluation indicators (Song et al., 2020b). For example, regarding positive emotions, the precision rate is the proportion of samples predicted to be positive sentiment that are truly positive sentiment. The proportion of all positive sentiment samples predicted to be positive sentiment is indicated through the recall rate. F1 is the harmonic mean of the precision rate and recall rate. Table IV shows the result of the evaluation index under different models, and the results show that Bi-LSTM performs best.

Table IV. The result of the evaluation index under different models.

Model	P	R	F1
RNN	0.7925	0.7801	0.7863
LSTM	0.8507	0.8350	0.8428
Bi-LSTM	0.8569	0.8573	0.8571

5.3 Regression analysis

This section uses SPSS software to perform regression analysis on the results obtained in Section 5.2 through multi-category disordered logistics regression to determine the topics that affect customers' positive, neutral and negative sentiments in cold chain logistics. Table V shows all the regression results. Combining Table V and formulas (14) and (15), the logistics regression model established in this research is obtained, as shown in formulas (16) and (17).

Table V. Results of regression analysis. (Number of reviews = 3512)

Independent variable	(a) Neutral sentiment		(b) Positive sentiment	
	B	Exp（B）	B	Exp（B）
Intercept	-16.147	-	-34.265	-
Speed	2.338**	10.360	2.550**	12.802
Price	2.106***	8.216	3.354***	28.607
Cold chain transportation	0.545	1.724	1.906**	6.726
Package	0.813	2.255	1.102	3.011
Quality	0.429	1.536	1.383**	3.988
Error handling	1.484*	4.411	1.037***	3.852
Service staff	-1.250	0.287	-2.213*	0.109
Information	0.604	1.829	1.470	4.351

$$\ln\left[\frac{p2}{p1}\right] = -16.147 + 2.388x_1 + 2.106x_2 + 0.504x_3 + 0.813x_4 + 0.429x_5 + 1.484x_6 -$$

$$1.250x_7 + 0.604x_8 \tag{16}$$

$$\ln\left[\frac{p3}{p1}\right] = -34.265 + 2.550x_1 + 3.354x_2 + 1.906x_3 + 1.102x_4 + 1.383x_5 + 1.307x_6 - 2.213x_7 + 1.470x_8 \tag{17}$$

Table V(a) shows the comparison of neutral sentiment and negative sentiment, and Table V(b) shows the comparison of positive sentiment and negative sentiment. In Table V(b), the coefficient of cold chain transportation is positively significant (coefficient: 1.906), indicating that cold chain transportation is a significant factor of positive sentiment rather than neutral or negative sentiment. Similarly, quality (coefficient: 1.383, significant) is also a significant factor influencing positive sentiment. The coefficient of the service staff is negative (coefficient: -2.213, significant), which indicates that the service staff factor is not a significant factor of positive sentiment but reflects negative sentiment. From Table V(a), it can be seen that speed (coefficient: 2.338, significant) may be a significant influencing factor of neutral sentiment rather than negative sentiment. The speed (coefficient: 2.550, significant) in Table V(b) also further illustrates that speed is not a significant factor of negative sentiment. Furthermore, comparing the Exp (B) value of speed (10.36<12.80) in Table V(a) and Table V(b), it can be seen that speed is most likely a significant factor affecting positive sentiment, less likely a neutral sentiment, and not a negative sentiment. The opposite of this situation is error handling (coefficient: 1.484 and 1.037, significant, 4.411>3.852), which is highly likely to be a significant factor of neutral sentiment, is rarely possible to be positive sentiment and is not a negative sentiment. Finally, package (coefficients: 0.813 and 1.102, nonsignificant) and information (coefficients: 0.604 and 1.470, nonsignificant) are not significant factors affecting sentiment polarity. Based on the above results, Table VI is obtained. Among them, speed, price, cold chain transportation and quality are significant factors that affect positive sentiment, error handling significantly affects neutral sentiment, and service staff is a significant factor for negative sentiment. Package and information are nonsignificant factors.

Table VI. Results of significance factors of different topics.

Independent variable	Negative sentiment	Neutral sentiment	Positive sentiment

Speed			Significant
Price			Significant
Cold chain transportation			Significant
Package			
Quality			Significant
Error handling		Significant	
Service staff	Significant		
Information			

6. Discussion

Improve product quality. Quality is a significant factor that affects positive sentiment, so ensuring quality is an important guarantee for improving customer satisfaction. Transportation, as an important part of logistics, has a vital influence on product quality. To maintain the freshness of cold chain products and reduce the rate of cargo damage, cold chain transportation is a necessary means. This point has also been verified in this research, where cold chain transportation has been proven to be a significant factor affecting positive sentiment. The application of refrigerated trucks to transportation can realize the cold chain transportation of products, but the transportation process is currently opaque, which leads to fraud. For example, to save cost, the driver may turn off the refrigeration equipment during transportation and turn it on again when the truck is almost at the destination, which reduces the quality of the product. Therefore, it is necessary to establish a whole-process supervision mechanism to monitor the temperature and location in the transportation process, which will enhance trust and promote the consumers' choice again. This point is also confirmed in this research. Specifically, although information (in-car temperature and location information) is not a significant factor, its influence coefficient is positive, indicating that information has a positive meaning in improving positive sentiment. Packaging has the same insignificant factor as information, and its influence coefficient is positive, which shows that good packaging can also promote positive sentiment.

Increase transportation speed. Speed is a significant factor that affects positive sentiment, and faster speed can enhance customer satisfaction. The customers in this research are supermarkets, and compared with ordinary consumers, they have higher requirements for timeliness. Therefore, the response to their demands must be rapid, which requires the seamless integration of the three links of order processing, shipping, and transportation, and efficient operation. At present, operational efficiency can be improved in two ways: one is the adoption of new technologies, and the other is the innovation of management methods. The application of modern technologies, such as the Internet of Things and Blockchain, has realized the intelligence and automation of work tasks, which improves response speed and shortens service time. However, for small and medium-sized enterprises, it is impossible to build an information platform in a short time. Therefore, it has become possible to improve service efficiency through management innovation, such as simplifying the procedures for product delivery and rationally arranging transportation routes.

Reduce transportation price. Table VI shows that price can significantly affect positive sentiment. The lower the price is, the higher the customer satisfaction. This requires enterprises to reduce their own operating cost, thereby setting lower service prices, which is conducive to forming a price advantage. However, speed and price are usually a pair of contradictory factors, which means that it is difficult for both to reach the optimal value at the same time. For example, enterprises can choose to arrange more vehicles to improve service speed and punctuality in transportation. However, the full load rate of vehicles in such scenarios is not high, which increases costs incurred by the enterprise and makes it impossible to provide customers with lower service prices. The development of information technology enables an effective resolution of this contradiction. The application of big data, the Internet of Things and Blockchain can optimize speed and cost at the same time. These technologies connect various physical nodes to realize the sharing of information and resources, which establishes a linkage and integrated distribution network to increase the service speed and reduce the cost from a global perspective.

Strengthen service management. Service staff is a significant factor influencing negative sentiment, which shows that poor service causes customer grief or anger. The customer service and delivery staff are service staff who directly contact customers, and they are the communication bridge between customers and the enterprise. The improvement of the customer service level benefits from pre-control and post-remedial measures. For pre-control, the enterprise should strengthen the professional skills of customer service staff so that they can quickly and accurately understand customer needs. Delivery staff can deliver goods to customers through standardized service processes, and they should all have the ability to quickly solve customer problems. For the post-remedial period, the enterprise should try to compensate for service failures that occur. The service staff should listen to the customer's statement, provide the customer with the necessary explanation, and apologize to the customers. For those who cannot be handled effectively, some compensation (gifts and coupons) should be provided to prevent the loss of customers.

Minimize error handling. Error handling is a significant factor of neutral sentiment, which shows that error handling can trigger both positive sentiment and negative sentiment. Therefore, the enterprise should deal with errors as quickly as possible to arouse the positive sentiment of customers, thereby motivating customers to continue choosing their products. First, the enterprise should simplify the return and exchange process. If the product has quality problems when the customer receives the product, it can be brought back directly by the delivery staff, without the need for the customer to contact customer service staff to explain the problem. Since customers have already complained about defected products, their complaints will be aggravated if the problem requires repeated explanations. Second, for products that are found to be problematic after receipt, the enterprise needs to perform efficient return and exchange processing, including contacting customers in a timely manner, giving customers a reasonable explanation, providing customers with solutions, and sending delivery staff to customers to collect the products.

In general, enterprises should strengthen the study of these factors (quality, speed, price and cold chain transportation) and their significant impact on positive sentiment to promote the formation of good customers' word-of-mouth endorsement. The service staff factor that significantly affects negative sentiment should be continuously improved to prevent the loss of customers. More attention should be paid to factors (error handling) that significantly affect neutral sentiment to cultivate a loyal customer group.

7. Conclusion remark

In this research, LDA model is used to identify the eight topics that customers concerned, including speed, price, cold chain transportation, package, quality, error handling, service staff and information. Further, the sentiment scores of the topics involved in the customer-generated reviews is calculated through the Bi-LSTM model. Lastly, regression analysis is carried out to determine the significant factors that affect customer sentiment. The results show that speed, price, cold chain transportation and quality significantly affect positive emotions. Error handling is a significant factor for neutral sentiment, and service staff is a significant factor for negative emotions.

7.1 Theoretical contributions

This research explores the factors that affect customer sentiment polarity in the cold chain logistics field, which provides an important reference for logistics and text mining related research. The theoretical contribution of this research is divided into three levels. First, in terms of information sources, this research has changed traditional data acquisition methods, including focus groups, expert interviews and questionnaire surveys. Instead, implementing customer-generated reviews as the source of data overcomes the shortcomings of the randomness of questionnaire data to ensure the authenticity of the data. Second, this research has made theoretical contributions to information conversion. One contribution is the use of LDA technology to determine the eight topics that affect customer sentiment polarity. To the best of our knowledge, this is an earlier research on the application of the LDA model to the field of logistics reviews. The second contribution is solving the key challenge of sentiment classification through the deep learning model. The Bi-LSTM model is used to carry out aspect-level sentiment analysis, which overcomes the disadvantage of the traditional LSTM that cannot learn the following content, and introduces a scoring mechanism to realize quantitative analysis of sentiment. To our knowledge, no research has applied the Bi-LSTM deep learning model to the field of logistics review analysis. Finally, in terms of information expression, this research uses a disordered multi-category logistics regression model to determine the significant factors that affect positive, neutral, and negative sentiments. It explores the relationship between the eight topics and sentiment polarity, which promotes research on customer sentiment in the logistics field. At the same time, this method can be extended to other online review fields to identify key influencing factors, including hotels, restaurants, travel and online shopping.

7.2 Managerial implications

The findings of this research provide practical enlightenment for practitioners in the logistics industry. Customer satisfaction is the focus of enterprises' attention, and high customer satisfaction can help enterprises form a loyal customer base, thereby maintaining a competitive advantage. This research helps logistics practitioners pay attention to the main aspects of the problem and make continuous improvements to them. According to the above results of this research, the following suggestions can be made for logistics practitioners. For improving customer positive sentiment, first, a full-process cold chain should be adopted to ensure product quality. At the same time, customers should be involved in the supervision of the transportation process to increase customer trust. Second, information technology (big data, Blockchain, and the Internet of Things) should be fully utilized, which can promote the sharing of resources and information to increase service speed and reduce distribution costs. Error handling plays an important role in stabilizing customer emotions, and logistics practitioners should deal with work errors in a timely and effective manner to prevent negative sentiment. To deal with the negative sentiment of customers, service staff must do a good job of diversion, explanation and apology to reduce the anger of customers, and proactively provide solutions to customers.

7.3 Limitations

Although the method proposed in this research has many advantages, there are still some limitations to be understood. First, the data of the customer-generated reviews in this research are in Chinese. In the future, multi-lingual research can be conducted to obtain more comprehensive insights. Second, it is recommended to apply other deep learning methods to sentiment analysis for comparison with the methods proposed in this research to clarify the best method. Finally, this research can be further extended to consider the factor of customer repeat purchases in the constructed model to explore the influence of customer sentiment polarity on customer repeat purchase behavior.

Appendix

Appendix, Table AI shows the key variables of the proposed methods, and Table AII show the sentiment labels.

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Appendix

Table AI. The key variables of the proposed methods.

Method	Symbol	Meaning
LDA	M	Number of documents
	N	Number of words
	K	Number of topics
	w	Word
	z	Topic to which a word belongs
	θ	Probability distribution of the document-topic
	ϕ	Probability distribution of the topic-word
	α	Hyperparameters of θ
	β	Hyperparameters of ϕ
Bi-LSTM	δ	Hyperbolic tangent function
	x_t	Current input
	h_{t-1}	Output of the hidden layer at the last moment
	f_t,	Forget gate
	i_t	Input gate
	o_t	Output gate
	c_t	A memory unit
	W_f	Weight matrices of the forget gate
	W_i	Weight matrices of the input gate
	W_o	Weight matrices of the output gate
	b_f	Biases of the forget gate
	b_i	Biases of the input gate
	b_o	Biases of the output gate
Regression analysis	J	Reference category of sentiment
	x_k	k- th independent variable
	β_{jk}	Regression coefficient of the independent variable

Table AII. The sentiment labels.

Topic	Topic labels (T)	Score label (S)	Sentiment label (E)
Speed	0	0	0
		1	1
		2	2
		3	3
		4	4
Price	1	0	5
		1	6
		2	7
		3	8
		4	9
Cold chain transportation	2	0	10
		1	11
		2	12
		3	13
		4	14
Package	3	0	15
		1	16
		2	17
		3	18
		4	19
Quality	4	0	20
		1	21
		2	22
		3	23
		4	24
Error handling	5	0	25
		1	26
		2	27
		3	28
		4	29
Service staff	6	0	30
		1	31
		2	32
		3	33
		4	34
Information	7	0	35
		1	36
		2	37
		3	38
		4	39

Note: “0, 1, 2, 3, 4” in the S represents the score of 1, 2, 3, 4 and 5 respectively.