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Exploring the Impact of Digital Shared Services in Finance on Corporate Treasurers' Job Anxiety

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Abstract

It has become a trend for enterprises to establish financial shared service centers for digital financial transformation, but the emotional impact of this transformation on the original financial staff of enterprises has been neglected. In this paper, we collect relevant intranet texts of enterprises, mine the emotions of the collected texts through the LDA theme algorithm, use the improved LSTM model to classify and identify the emotions of the collected texts, and construct the LDA-BiLSTM sentiment analysis model to analyze the anxiety condition of the financial staff of enterprises. The efficiency of LDA can be improved by using the weighted median to deal with outliers. Two LSTM networks are combined to form a BiLSTM network to improve the problem of inaccurate judgment of sentiment indicators by a single LSTM. Finally, the model is used to empirically analyze the emotions of financial staff before and after the transformation of an enterprise's financial digital service. Negative feelings that are linked to anxiety have an accuracy rate of 95.23%. The frequency of separation after the transition was as high as 0.5, and the frequency of dismissal was as high as 0.423. Overall sentiment scores were lower than 0.7. After the transition, the number of people worried about negative feelings related to anxiety rose from 32% to 64%. Finance professionals are experiencing a significant increase in anxiety due to the post-transition of the enterprise.

Keywords: LDA topic algorithm; BiLSTM; Weighted median; Sentiment analysis; Finance digital shared services.
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1 Introduction

Anxiety is a common emotion in daily life and workplace development. When anxiety is present, the individual feels emotionally irritable and worried, as well as experiencing a physiological response of chest tightness and trembling [1-2]. Included in this emotion is usually the individual's expectation of freedom from the fulfillment of an ominous premonition, as well as a sense of powerlessness. [3]. Individuals who are experiencing high levels of anxiety tend to seek out extremes like sure things or unsure adventures to feel more comfortable [4]. In evolutionary psychology, it is believed that an appropriate level of anxiety is beneficial for an individual's survival and development, but excessive anxiety can be detrimental to an individual.

The development of digital technology provides strong support for financial organizations to optimize processes, improve business performance, and enhance competitiveness [5]. Although the use of digital technology helps to improve employee performance, it is a double-edged sword, and employees suffer from being surrounded by a large number and complexity of information technology [6]. The use of information technology not only brings the positive side but also has the potential to bring the negative side. Digital shared services make work constantly "invade" employees' lives, creating "technology invades life" stress [7-8]. Some studies have found that individual stress is related to negative emotions, and when individuals feel stress, it can cause negative emotions such as anxiety, depression, and anxiety [9].

In previous studies, most of them studied the relationship between digital technology intrusion into life as a dimension of technology stressors and its relationship with outcome variables, and few scholars explored the effects of the dimensions of digital stressors on employees' work anxiety separately. Literature [10] used 1,783 healthcare workers in South Korea as study subjects and found that nurses with work stress had significantly higher levels of anxiety symptoms compared to general practitioners ($p < 0.01$), suggesting that there is a significant association between employee anxiety and work stress. Literature [11] explored the relationship between job anxiety and digital technology among online employees through factor analysis and structural equations and found that digital technologies such as email, phone calls, and video conferencing lead to significant anxiety among employees.

Literature [12] found through empirical investigations that employees' fear of negative evaluations and social evaluations are both major contributors to employees' anxiety and that employees' fear of negative evaluations during supervisory performance ratings is positively correlated with social evaluation job anxiety. Literature [13] explored the relationship between information overload on ESM and employee workplace anxiety under enterprise social media (ESM) by developing a theoretical model, which was tested using PLS-SEM, and the results showed that ESM information overload was positively correlated with work anxiety. Literature [14] explored the mediating role between job fear anxiety on employees' job alienation using multi-source data in a quantitative time-lag design, and they found that a sense of organizational support exerted a significant buffering effect between role stress and stressful outcomes (performance, satisfaction, and retention).

In this paper, we develop a sentiment analysis model that utilizes both LDA text mining and LSTM deep learning techniques. Firstly, we use the weighted median to deal with outliers and utilize the improved zero-space method to deal with the small-sample problem as well as the intra-class scatter matrix singularity problem to construct the 3E-LDA model. Then, the Bi-LSTM model is formed by using two LSTM models with different directions. This is where the LDA-BiLSTM sentiment analysis model is established from. After the model design is completed, the annotated corpus of microblogging is used to train it, a negative vocabulary corpus is established, and it is used in an enterprise for practical use, data cleaning is carried out after acquiring the data, the LDA topic model is used to classify the topic of the text data, and finally, the analysis of the textual sentiment tendency is carried out based on the BiLSTM model. Examine how the transformation of enterprise finance to a digital shared service affects the work anxiety of personnel in enterprise finance.

2 The application of sentiment analysis model in analyzing the job anxiety of finance personnel

Through social media or questionnaires, users post a large number of comment texts on an event, which provides the possibility of mining the evolution of user sentiment. Big data analysis is commonly accompanied by the use of LDA text mining techniques and sentiment analysis methods. Topic mining techniques can recognize the user’s state from a large amount of comment text data, and sentiment analysis methods can get the emotional tendency of the text from a large amount of comment text data. Traditional machine learning is unable to make accurate recognition and prediction because of the large text noise, but the emergence of deep learning makes up for this shortcoming. LSTM shows good performance in sentiment analysis, and in this paper, we choose to combine it with LDA mining technology to explore the impact of financial digital shared services on the work anxiety of corporate finance personnel.

2.1 Application of LDA Text Mining Techniques for Sentiment Analysis

Sentiment polarity classification can only know the subject’s emotion or attitude towards the evaluation object from the overall perspective, but because the target of the sentiment polarity information may not be the whole review object, there may be many parts that constitute the whole review object, and these parts are called the themes, so the extraction of the themes and the sentiment analysis is also more important. LDA is applied here.

Let the sample set be: $\mathbf{X}=\left[\mathbf{x}_1,\mathbf{x}_2,\cdots,\mathbf{x}_n\right]^{\mathrm{T}}\in\mathbf{R}^{n\times m}$, where x_s is a m-dimensional vector, $s=1,2,\ldots,n$, n denote the total number of samples. Let the sample set contain C classes. x_j^i denotes the jth sample of class i, $i=1,2,\ldots,C, j=1,2,\ldots,n_i$, where n_i denotes the total number of samples in class i, and $n=\sum_{i=1}^{c} n_i$.

The mean of the samples of class i is defined as $\mu^i=\frac{1}{n_i}\sum_{j=1}^{n_i} x_j^i$ and the mean of the dataset is defined as $\mu=\frac{1}{C}\sum_{i=1}^{C}\mu^i$. From this, the intra-class scatter matrix S_ω and inter-class scatter matrix S_b can be computed as shown in equations (1)-(2), respectively:

$$S_\omega=\sum_{i=1}^{c}\sum_{j=1}^{n_i}\left(x_j^i-\mu^i\right)\left(x_j^i-\mu^i\right)^T \tag{1}$$

$$S_b=\sum_{i=1}^{c} n_i\left(\mu^i-\mu\right)\left(\mu^i-\mu\right)^T \tag{2}$$

Thus the optimal discriminant matrix q can be calculated by Eqs. (1)-(2) as shown in Eq. (3):

$$q = \arg\max_q J(q) = \arg\max_q \left(\frac{q^T S_b q}{q^T S_\omega q} \right) \tag{3}$$

Finally, the derivation of Eq. (3) can be transformed into an eigenvalue solution problem for $S_\omega^{-1} S_b q = \lambda q$, where $\lambda = J(q)$ is a scalar. To address the 3 drawbacks of traditional LDA, 3E-LDA proposes the following improvements.

Let the weight vector of the j nd sample of class i be $w_j^i = \left[abs\left(x_j^i - \mu_m^i \right) + \beta \right]^{-1}$, where $abs(\cdot)$ denotes the absolute value of the given vector in each dimension, β is a vector of compensating factors, aligned with the vector x_j^i, and μ_m^i shows the median of all the samples of class i. The weight vector w_j^i of the x_j^i samples is inversely proportional to the distance between x_j^i and μ_m^i. Thus the weighted median value of the sample for category i can be obtained as shown in equation (4):

$$\tilde{\mu}^i = \left(\sum_{j=1}^{n_t} w_j^i \square\ x_j^i \right) ./ \left(\sum_{j=1}^{n_t} w_j^i \right) \tag{4}$$

3E-LDA proposes a new scatter matrix framework. The intraclass scatter matrix $S_{i\omega}$. Let x_j^i and x_k^i be two samples of class i, and if x_k^i is one of the K nearest neighbors of x_j^i, then x_j^i can be x_k^i approximated linearly as $\hat{x}_j^i = \sum_{k=1}^{K} w_{jk} x_k^i$. Substituting $\hat{x}_j^i$ and the weighted median $\tilde{\mu}^i$ into the above equation yields $S_{i\omega}$ as shown in equation (5):

$$S_{i\omega} = \sum_{i=1}^{C} \sum_{j=1}^{n_t} \left(\hat{x}_j^i - \tilde{\mu}^i \right) \left(\hat{x}_j^i - \tilde{\mu}^i \right)^T \tag{5}$$

Interclass Scatter Matrix S_{ib}. From the above equation, it can be seen that if the value of $(\mu_i - \mu)$ is larger, the class i samples play a dominant role in S_b, which will result in overlapping classes with similar distances. Therefore the above equation can be rewritten:

$$S_b = \sum_{i=1}^{C} n_i \left(\mu^j - \mu \right) \left(\mu^i - \mu \right)^T = \sum_{i=1}^{C-1} \sum_{j=i+1}^{C} \frac{n_i n_j}{n} \left(\mu^i - \mu^j \right) \left(\mu^i - \mu^j \right)^T \tag{6}$$

where n_i and n_j denote the total number of samples in categories i and j, respectively. The penalty term is set to $c_{ij} = \left(\left\| \mu^i - \mu \right\|_2 + \varepsilon \right)^{-1}$. Substituting the weighted median $\tilde{\mu}^i$ and penalty term c_{ij} into Eq. (2) yields S_{ib} as shown in Eq. (7):

$$S_{ib} = \sum_{i=1}^{C-1} \sum_{j=i+1}^{C} \frac{n_i n_j}{n} c_{ij} \left(\tilde{\mu}^i - \tilde{\mu}^j \right) \left(\tilde{\mu}^i - \tilde{\mu}^j \right)^T \tag{7}$$

The improved zero-space method is used to deal with the small sample problem and the problem of the singularity of the scatter matrix within the class: if the rank r of $S_{i\omega}$ is less than the dimension m of the original data space V, then there must exist a subspace $V_0 \subset V$ such that $V_0 = span\{v_i \mid S_\omega v_i = 0, i = 1, 2, \ldots, m-r\}$. The singular value decomposition of $S_{i\omega}$ yields $V = [v_1, \ldots, v_r, v_{r+1}, \ldots, v_m]$, where: $V_1 \subset V, V_l = [v_{r+1}, \ldots, v_m]$. Thus the optimal discriminant matrix q is the set of maximal eigenvalues of $V_1 V_1^T S_{ib} \left(V_1 V_1^T\right)^T$ in V_0, which is otherwise solved according to the Fisher criterion.

Thus, the complete objective function of 3E-LDA can be shown in the following equation:

$$\arg\max J(q) = \begin{cases} \dfrac{q^T S_{ib} q}{q^T S_{i\omega} q}, r = m \\ q^T V_1 V_1^T S_{ib} \left(V_1 V_1^T\right)^T q, r < m \end{cases} \tag{8}$$

where the optimal discriminant matrix $q \in R^{m \times (C-1)}$.

2.2 LSTM Modeling Applied to Sentiment Propensity Analysis

The framework of the LSTM neural network model is shown in Figure 1. An LSTM neural network model framework includes a memory unit state $c(t)$, an input gate $i(t)$, a forgetting gate $f(t)$, and an output gate $o(t)$. Among them, $i(t)$ is used to determine the number of input values $x(t)$ at time t that can be saved to memory unit $c(t)$, $f(t)$ is used to determine the number of memory units $c(t-1)$ at time $t-1$ that can be retained to memory unit $c(t)$ at time t, and $o(t)$ is used to determine the output value $h(t)$ in $c(t)$ at time t that can be output to the LSTM neural network model. Next, the work flow of LSTM neural network model is explained.

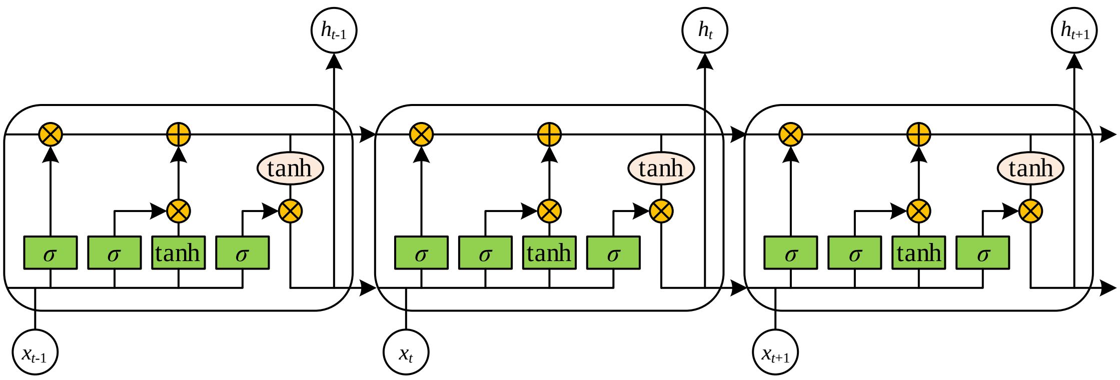

Figure 1. LSTM neural network model framework

The first step of the modeling process begins with the selection of the input information controlled by the forgetting gate $f(t)$. The forgetting gate outputs a value between 0 and 1 for the memory cell $c(t-1)$ at moment $t-1$ by processing the output value $h(t-1)$ at moment $t-1$ with the input value $x(t)$ at moment t. A value of 0 indicates that the information is completely discarded, and a value of 1 indicates that the information is completely retained. The expression is as follows, where W_f is the weight of the output and b_f is the bias term:

$$f(t)=\sigma\left(W_f[h(t-1),x(t)]+b_f\right) \tag{9}$$

The second step of the model is the introduction of the second step of the process of the input gate and the process of the memory unit. As shown in Fig. 1, the input gate includes two activation functions, *sigmoid* and tanh. The *sigmoid* function is responsible for updating the information and the tanh function is responsible for generating new candidate values. The mathematical expression of the work is:

$$i(t)=\sigma\left(W_i[h(t-1),x(t)]+b_i\right) \tag{10}$$

$$C'(t)=\tanh\left(W_c[h(t-1),x(t)]+b_c\right) \tag{11}$$

The memory cell after performing the update is $C(t)$ and its mathematical expression is:

$$C(t)=f(t)\odot C(t-1)+i(t)\odot C'(t) \tag{12}$$

Finally, after the workflow of forgetting gate and input gate, the output gate outputs the result. And the final output value of the LSTM neural network model is determined by the output gate and the memory unit together, the specific formula is shown below:

$$o(t)=\sigma\left(W_o[h(t-1),x(t)]+b_o\right) \tag{13}$$

$$h(t)=o(t)\odot\tanh(C(t)) \tag{14}$$

2.3 Construction and operation procedure of LDA-BiLSTM analysis model

The model structure of BiLSTM is shown in Fig. 2. BiLSTM consists of a forward LSTM and a backward LSTM, and ultimately these two LSTMs in opposite directions determine the output result, which can capture the semantic dependencies over longer distances in both directions compared to LSTMs.

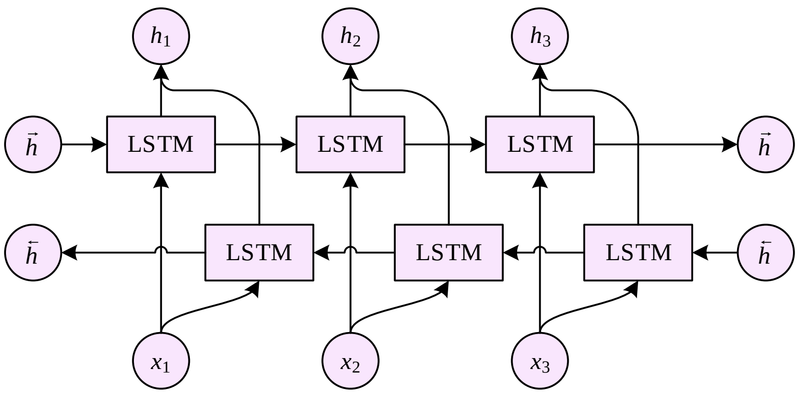

Figure 2. The model structural diagram of BiLSTM model

As can be seen from Fig. 2, BiLSTM can learn information $\overrightarrow{h_t}$ above and information $\overleftarrow{h_t}$ below, after which information $\overrightarrow{h_t}$ above and information $\overleftarrow{h_t}$ below can be spliced and activated using the relu function, then there is Eq:

$$\overrightarrow{h_t} = \tanh\left(C_t\right) * \sigma\left(W_o^{(l)} \cdot \left[\overrightarrow{h_{t-1}}, x_t\right] + b_o\right) \tag{15}$$

$$\overleftarrow{h_t} = \tanh\left(C_t\right) * \sigma\left(W_o^{(r)} \cdot \left[\overleftarrow{h_{t-1}}, x_t\right] + b_o\right) \tag{16}$$

$$h_t = relu\left(W_t\left(\overrightarrow{h_t}, \overleftarrow{h_t}\right) + b_t\right) \tag{17}$$

The framework of text theme and sentiment analysis proposed in this paper is shown in Fig. 3, which consists of four parts. The first step is data acquisition, obtaining data through questionnaires or Python software to get the required material. The subsequent step is data preprocessing and cleaning, which involves reducing the weight of text data, splitting Chinese words, removing deactivated words, and others. The third step involves theme identification, which involves determining the number of themes using confusion degree and then using the LDA theme model to classify them in the text data. The last step is sentiment analysis, which is based on the BiLSTM model to analyze the sentiment tendencies of the text.

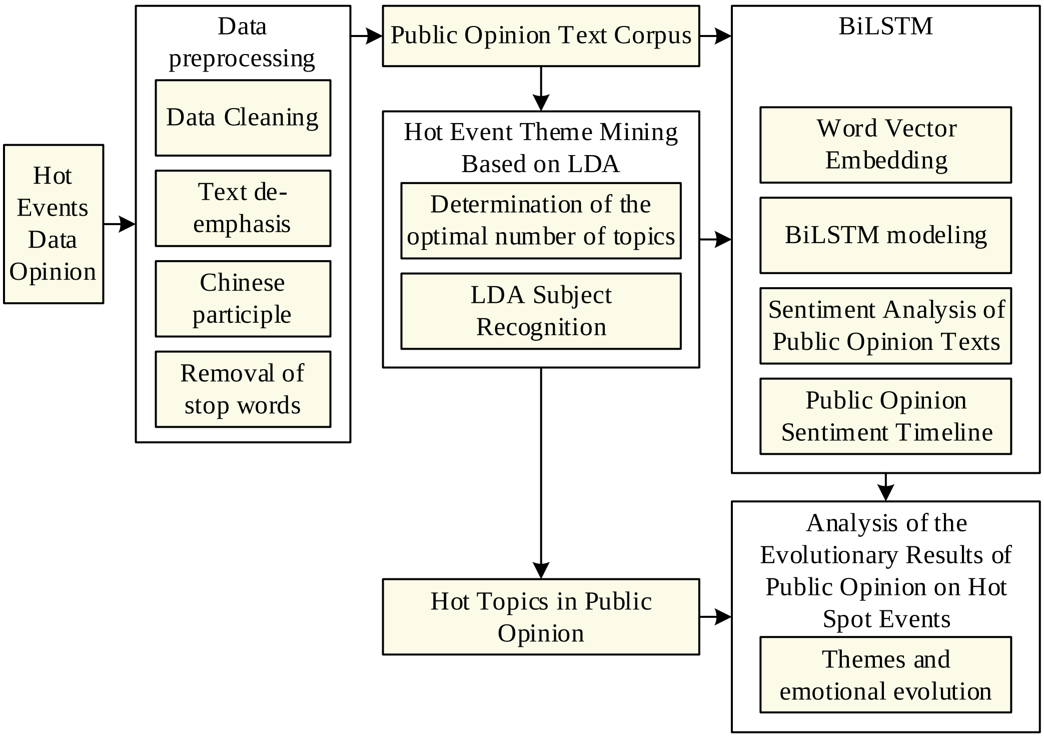

Figure 3. Text theme and emotional analysis framework

3 The emotional impact of financial digital shared services on corporate finance personnel

3.1 Analysis of model sentiment training results

This chapter is going to use a supervised sentiment analysis algorithm model, so the first step is to train the deep learning model using a corpus package that has been labeled with sentiment states, to obtain a sentiment classification model with good predictive performance, to predict the sentiment tendency of unlabeled corporate finance personnel.

A good classification model needs to obtain a sufficiently large number of corpus to be repeatedly trained, but also needs to have a close correlation between the training data and the predicted data content, so this paper first obtains a total of 38,674 labeled corpus about the work, of which 8,572 are positively evaluated and 38,672 are negatively evaluated. It is more appropriate to use it to train the model.

The collected text data of the corpus is divided into training sets, validation sets, and test sets according to 7:2:1 and ensure that the positive and negative labels are evenly distributed in each data set. The training set is used to estimate the model, then the validation set is used to determine the network structure, and finally, the test set is used to test the model. The corpus packet data is then preprocessed for segmentation and deactivation of words, etc. Table 1 shows the operation of the model.

It can be seen that Bathch size of 16 has the highest accuracy of 95.23% and F1 value of 88.12% but consumes the time of 1582 s. Batch size increased to 256 consumes the shortest time of 496 s but accuracy decreases together to 93.44%.

Table 1. BiLSTMExperimental results of emotional analysis model

Bathch_size	F1(%)	Accuracy(%)	Times
16	88.12	95.23	1582
32	89.68	94.58	938
64	90.45	94.29	604
128	91.29	94.16	587
256	92.16	93.44	496
Performance parameter	Accuracy	Recall rate	
Positive emotion	91.58%	0.902	
Negative emotion	95.23%	0.874	
Parametric mean	92.52%	0.819	

The datasets required for deep neural network model training are very large, during the experiment the whole training set will be put into the model in batches for training, then the model will compare the output obtained with the actual values, calculate the loss function, and finally update the model parameters by backpropagation, which completes one iteration. From the above table, we can see that the accuracy rate of positive feelings is 91.58%, and the accuracy rate of negative feelings is 95.23%, and the model will use the updated parameters as the initial parameters for the next iteration, and so on. Overall the model's learning status is good, and next it will be applied to the emotions of the finance staff of a company after the sharing transformation to analyze their work anxiety status.

3.2 Emotional analysis of digital shared service transformation in finance

This paper collects and organizes public data from the intranet of a company after its financial digital transformation from 2020, to 2013. The top 10 high-frequency words statistics were analyzed using the LDA model. Table 2 shows the statistics of high-frequency words. It can be seen that the most discussed keyword is financial sharing, with a total of 8,475 times. The second most talked about keyword is separation from work, which is as high as 8251 times, and anxiety-related dismissal, stress, fear, and anger are also in the top 10, with counts of 7648, 7483, 6360, and 3857 times, respectively.

Table 2. A company's high frequency word statistics

Word	Frequency	Word	Frequency
Financial sharing	8475	Job hunting	4958
Leave the office	8251	Financial personnel	4647
Dismissed	7648	Endangerment	4285
Pressure	7483	Transition	4120
Be afraid of	6360	Management	3968
Efficiency	5423	Get angry	3857
Company transformation	5301	Efficiency	3642

The purpose of this paper is to categorize the data more intuitively, by dividing all the high-frequency words into five themes and grouping all the words related to anxiety into one category. Table 3 shows the vocabulary embedded in the themes. TOP1 is almost exclusively negative affective vocabulary. TOP3 is on the contrary a positive affective vocabulary group.

Table 3. Subject word distribution

Subject	Word1	Word2	Word3	Word4	Word5	Word6
TOP1	Leave the office	Dismissed	Be afraid of	Pressure	Get angry	Job hunting
TOP2	Financial sharing	Company transformation	Financial personnel	Efficiency	Efficiency	Transition
TOP3	Introduction	Employment	Joyfulness	Promotion	Pleasure	Pay
TOP4	Off duty	Game	Sing	Football	Basketball	Eat
TOP5	Organization	Management	Talent	Company	Enterprise	Earnings

Using LDA to calculate the frequency of occurrence in TOP1~5, the frequency distribution of the top 6 popular words under 5 themes is presented in a more concise and easily comparable form. Figure 4 shows the probability distribution of the topic words. in TOP1, the frequency of leaving a job is as high as 0.5, and the frequency of dismissal is as high as 0.423, while the average frequency of TOP3 is less than 0.5, and only word 2 has the highest frequency of 0.42. This suggests that after the transformation of the enterprise into a digitalized shared service for financial services, the anxiety-related words have the highest probability of appearing in the topics of the employees, and have already become the hot topic of the employees' discussion. Hot topics.

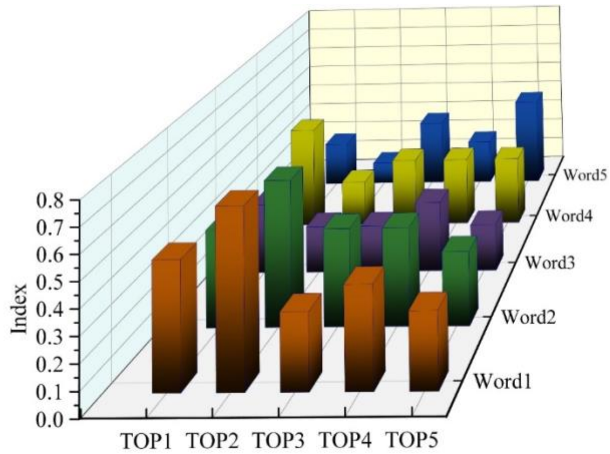

Figure 4. The probability distribution of the theme word

Through the Bi-LSTM sentiment classification model constructed in the previous section, using the user microblog text that has been preprocessed, the sentiment tendency of a company's financial personnel is judged, and the sentiment analysis results of each user are summarized, and the proportion of negative sentiment is obtained by calculating, and the results are written into the user data table. Table 4 shows the summary of topic emotions, and further descriptive statistics are carried out according to the characteristics of the obtained negative emotion proportion, from which it can be seen that the proportion of negative emotions of users. The TOP1 proportion is basically at 0.54, and the highest value reaches 0.91. The average value of the TOP4 that expresses ease of use is only 0.21. In addition to posting content such as leaving the company and looking for a job, it also expresses part of the negative content, and the contents of anger, stress, and fear are also included. It has been observed that certain employees display more negative emotional traits, which could be influenced by their personality traits and life circumstances.

Table 4. Emotional distribution

Subject	Mean	Std	Min	20%
TOP1	0.54	0.18	0.21	0.36
TOP2	0.31	0.15	0.16	0.35
TOP3	0.36	0.14	0.14	0.29
TOP4	0.21	0.19	0.09	0.28
TOP5	0.15	0.13	0.13	0.21
Subject	40%	60%	80%	Max
TOP1	0.41	0.53	0.61	0.91
TOP2	0.37	0.39	0.54	0.64
TOP3	0.31	0.35	0.49	0.59
TOP4	0.35	0.38	0.54	0.64
TOP5	0.28	0.31	0.63	0.73

The number of sentiments of the finance staff of a company is plotted as a graph. Figure 5 shows the sentiment analysis fluctuation. From the figure, it can be seen that the overall distribution of the fluctuation curve is lower, and with the increase in the number of comments more and more stable in the lower side of the interval, it can be seen that most of the corporate finance staff on the evaluation of the digital shared services is also a negative attitude. It can be seen that the overall sentiment score is lower than 0.70. As the number of comments increases, the likelihood of its sentiment score declining increases. When the number of comments is 600 the lowest drop is 0.432. When the number of reviews is 200-300 the reviews appear high, with the highest score of 0.832, but it drops quickly.

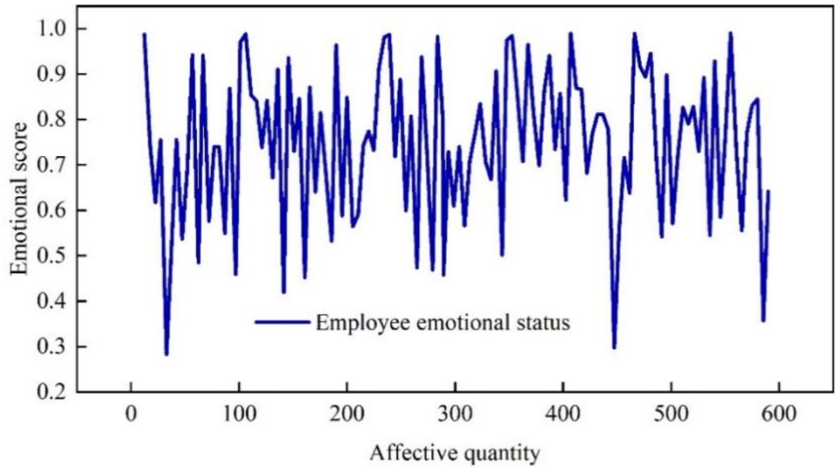

Figure 5. Affective analysis wave chart

Analysis from the perspective of the current corporate financial shared service center, after the active implementation of financial shared services on the current financial staff to produce a greater impact, resulting in a reduction in the relevance of financial staff and business departments, it is difficult to fully understand the actual situation of the business, reducing the level of business capacity of the enterprise's financial staff, purely from the data point of view of the analysis of the judgment, while the financial shared center is based on a standardized management model. Results in financial personnel needing to deal with a variety of repetitive financial statement data every day, showing a mechanized situation, the workload is heavier, the work content is boring, easy to causes the staff themselves to lose their enthusiasm for work, and ultimately increase the overall risk of error, and even the loss of talent, reducing the competitiveness of enterprises.

3.3 Before and after analysis of the transformation of the company's financial digital shared services

Since the company started its finance digital transformation in 2020, cleaning only its post-transformation data as well as sentiment analysis only proves that corporate finance staff hold negative sentiments towards digital shared services. If we want to fully understand the impact of corporate finance digital shared services on job anxiety among finance staff, we also need to investigate the data before the company's transformation. To this end, this paper seeks the consent of enterprise managers to crawl a company's intranet comment data by using the model in this paper, spanning from January 17, 2018, to December 13, 2020, to form a total of 12,912 pieces of initial comment data, followed by a cleaning operation on the data, removing the useless feature columns, eliminating the duplicated data as well as the comment data that is invalid for the analysis, and finally obtaining the valid comment data of 10239, according to the existing labeled comment data on the existing new data labeling operation, the formation of sentiment data set with labeling.

With the help of the LDA theme model financial staff work comments implied in the theme, to understand the actual situation of the employee's emotions, this paper uses the Gensim toolkit to construct the LDA theme model, the cleaned dataset is imported into the LDA theme model, according to the theme perplexity, after many samples and repeated tests, when the number of themes is 5, and the theme word under each theme is 10, the best effect. The distribution matrix of topic words and probabilities within the course review text can be found in Table 5. From the table, it can be seen that the probability of TOP1 is not high overall when it comes to 2018~2020. The occurrence probability of separation is only 0.054, which is lower than the happy 0.061 of Word3 in TOP3. The probability of TOP3 is higher overall, higher than 0.05. TOP5 has a higher level of discussion, as can be observed.

Table 5. Text theme - probability distribution matrix

TOP1		TOP2		TOP3		TOP4		TOP5	
W	P	W	P	W	P	W	P	W	P
Leave	0.054	Finance	0.025	Introduction	0.063	Off duty	0.063	Organization	0.075
Dismissed	0.051	Transition	0.016	Employment	0.072	Game	0.026	Management	0.069
Afraid	0.032	Talent	0.019	Joyfulness	0.061	Sing	0.018	Company	0.052
Pressure	0.029	Efficiency	0.031	Promotion	0.075	Football	0.013	Enterprise	0.047
Angry	0.019	Hoisting	0.021	Pleasure	0.081	Basketball	0.012	Earnings	0.065
Job hunting	0.015	Situation	0.013	Wages	0.091	Eat	0.019	Revenue	0.046

After extracting the topic from the text, the attention of each topic is computed using Bi-LSTM to obtain the evolutionary trend graph by analyzing the temporal change in attention for each topic. Figure 6 shows the evolution of the attention to the five themes. From 2018 to 2023 TOP3 Positive Emotional Relevance declines linearly. The curve of the opposite style TOP1 Anxiety Emotion Related starts to rise gently from 2018. By 2020, it begins to increase abruptly, with the concern increasing from 32% to 64%. After companies undergo a finance digital shared services transformation, finance staff job anxiety rises significantly.

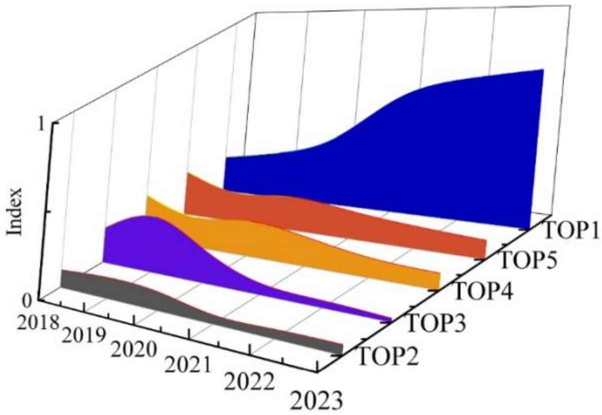

Figure 6. The focus of the theme is evolving

3.4 Recommendation

The enterprise finance shared service center is not the only benefit. For the enterprise financial shared service center, the construction process is prone to financial risks, especially in the early public construction process, the need to invest in human resources and financial resources, resulting in the overall investment costs, but also includes the corresponding site costs, travel costs, equipment costs, resulting in a reduction in the economic benefits of the enterprise itself. At the same time in the financial shared service center, you need to face the related equipment inspection, information updating, and other costs, resulting in increased costs in the early stage, the later economic benefits usually difficult to achieve the expected results, creating the enterprise's debt, and even the formation of economic crisis. For enterprise financial personnel, low-end financial personnel are replaced by information technology, resulting in layoffs. Leaving other financial personnel in the enterprise will also cause significant anxiety. In addition, after the centralized management of financial sharing, the content of its services has been significantly transformed from the original front-end into the back-end, and its sensitivity is reduced, which may result in ineptitude, thus further generating a sense of anxiety. Based on the highly integrated information, there are more management loopholes, which can easily cause management risks, and to a certain extent increase the difficulty of management, which is not conducive to enterprise development.

4 Conclusion

In this paper, we use the LDA-BiLSTM model to analyze the sentiment of the finance staff of an enterprise to explore the emotional impact of the digital shared service of enterprise finance on the staff of the enterprise, and draw the following conclusions:

The accuracy of the model in this paper is relatively high, with the highest accuracy of 95.23% when the Bathch size is 16, and the F1 value is 88.12%, but the consumed time is 1582 s. With Batch size increased to 256, the consumed time is the shortest at 496 s, but the accuracy rate drops to 93.44% at the same time. The probability of negative emotions is not high overall from 2018 to 2020 before the transition. The probability of leaving a job is only 0.054. The frequency of leaving a job in post-transformation negative emotions is as high as 0.5, and the frequency of dismissal is as high as 0.423. The TOP1 concern of the negative emotion discourse set in post-transformation enterprises has risen from 32% to 64%. Sentiment scores for finance staff, as a whole, are below 0.70. The sentiment scores of comments tend to be lower when there is a greater number of them. The lowest drop to 0.432 scores when the number of comments is 600. It can be demonstrated that the digital transformation of corporate finance has significantly increased staff anxiety.

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