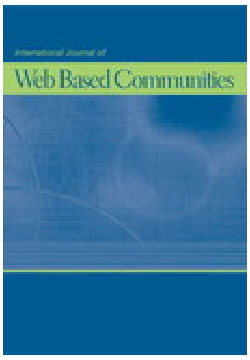

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A method for identifying consumer emotional tendency in the 'live streaming+e-commerce' mode

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Abstract: In order to achieve accurate and rapid identification of consumer emotional tendencies, a method for identifying consumer emotional tendencies under the 'live streaming+e-commerce' mode is proposed. Firstly, classify the emotional tendencies of consumers under the 'live streaming+e-commerce' model, mainly into two categories: positive and negative. Secondly, based on the comment data of e-commerce live streaming platforms, construct a benchmark vocabulary of emotional tendencies. Finally, a combination of HowNet similarity and Google similarity is used to identify consumers' emotional tendencies. The experimental results show that compared with existing methods, the accuracy of consumer sentiment orientation recognition in this method is significantly improved, and the recognition time is significantly shortened, and the recognition accuracy remains above 90%.

Keywords: the 'live streaming+e-commerce' model; consumer; emotional orientation identification; HowNet similarity; Google Similarity.

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1 Introduction

With the rapid development of the internet, live streaming and e-commerce have gradually become one of the main ways for consumers to shop. The live streaming +e-commerce model combines real-time live streaming with online shopping, providing consumers with a more convenient and interactive shopping experience (Meng et al., 2021). In this mode, consumers can watch product displays on live streaming platforms, interact with anchors, and make purchases directly during the live streaming process. The rise of this model not only changes the traditional offline retail model, but also brings consumers a brand new shopping experience. Identifying consumer emotional tendencies is of great significance for the development of the live streaming+e-commerce model and the formulation of marketing strategies. By accurately identifying consumers' emotional

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tendencies, we can understand their attitudes and preferences towards the live streaming+e-commerce model, and then improve and optimise products, services, and marketing strategies in a targeted manner to enhance consumers' shopping experience and satisfaction (Yue and Lu, 2021; Dong et al., 2022; Addo et al., 2021). In addition, studying consumer emotional tendencies can also provide valuable market information and user feedback for live streaming and e-commerce platforms. By analysing consumers' emotional tendencies, we can understand their preferences for different products and anchors, thereby providing targeted recommendations and personalised services for the platform, improving user stickiness and platform activity (Lin, 2021). Therefore, studying methods for identifying consumer emotional tendencies under the live streaming+e-commerce model has important theoretical and practical significance. It can not only provide reference for enterprises to formulate more effective marketing strategies, but also promote the healthy development of the live streaming+e-commerce model.

Li et al. (2023) proposed an e-commerce platform consumer emotional orientation identification method based on graph neural network and attention. This method uses graph neural network and two-way short-term memory network to classify emotional signals, and uses Dempster Shafer evidence theory fusion to complete the classification and identification of consumer emotions. However, this method has the problem of insufficient identification accuracy. Wang et al. (2021) proposes a method for identifying emotional tendencies of e-commerce platform consumers based on key causal connections of transfer entropy. This method uses transfer entropy causal analysis to construct a normalised transfer entropy matrix for emotions, and subtracts the neutral emotion matrix from it. Finally, a simplified emotional transfer matrix is used to analyse emotional signals and complete the identification of consumer emotional tendencies. However, this method involves a large number of matrix simplification steps, resulting in a longer overall emotional orientation identification time. Lin et al. (2021) proposes a multi task learning based method for identifying consumer emotional tendencies on e-commerce platforms. This method uses the multimodal shared layer in the multi task learning model to extract emotional signal features and construct a consumer emotional tendency identification model. The output of the model is the emotional tendency identification result. However, the identification accuracy of this method still needs further improvement.

In order to solve the problems of low identification accuracy and long identification time in existing emotional orientation identification methods, this study proposes a new consumer emotional orientation identification method under the 'live streaming+ e-commerce' mode.

2 Consumer sentiment analysis under the 'live streaming+e-commerce' model

In recent years, live streaming e-commerce has rapidly risen, becoming a remarkable economic development and social phenomenon. So, what are the psychological and motivational factors for consumers to choose this consumption model? This study aims to analyse and summarise consumers' consumption emotions under the 'live streaming +e-commerce' model.

1 Firstly, it is applicable to consumption. Live streaming e-commerce is suitable for consumers who want to save time and cost in purchasing products and hope to obtain high-quality products at lower prices. This consumer psychology was already very common in the early days of live streaming e-commerce. Therefore, the main needs of customers are to save time and obtain more cost-effective products.

2 The second category is social media consumption. E-commerce live streaming can not only improve the applicability of shopping experience, but also meet consumers' needs in social media, ultimately leading to shopping behaviour. Merchants skip monotonous product introductions through real-time interaction with customers, allowing consumers to understand how anchors provide detailed product introductions and other users' evaluations and discussions of the product. In addition, throughout the entire live broadcast process, users can also engage in bullet screen interactions with network anchors and other netizens, obtain information about products, and participate in subsequent topic discussions and exchanges. After shopping, users can also share their usage experience to meet their comprehensive needs for social media (Envelope et al., 2022; Wang et al., 2022).

3 The third type is 'fan' consumption. Users of live streaming e-commerce platforms often choose to purchase products not because of their price and applicability, but because of their pursuit of celebrities and becoming consumers. In recent years, due to the influence of the global environment and the film and television industry, more and more celebrities have joined the ranks of live streaming sales. Although these celebrities did not engage in excessive promotion on social media, they were still able to generate high sales through their own popularity and controversy. In fact, a large number of cases and data indicate the enormous potential and irrelevance of the 'fan' economy (Gu et al., 2022).

4 The fourth type is situational consumption. Shopping has become an important habit in people's daily lives, and even if there is no need to purchase any goods, many consumers still consider strolling as a pleasure. Watching live broadcasts of 'celebrities' in virtual spaces has become a special way of shopping. Customers who enter the live broadcast room can feel the joy of shopping even if they have not purchased anything. The live streaming e-commerce platform provides a shopping environment that simulates real-life scenarios, allowing customers to watch anytime in their free time. For them, the number of orders submitted is not the most important, but rather creating an online shopping experience.

5 The fifth category is emotional consumption. Personal behaviour is usually influenced by personal emotions, which determine whether to purchase a certain product. E-commerce platforms have opened live streaming rooms to assist in marketing agricultural products. Such live streaming e-commerce has gained identification from netizens and achieved profits. For example, online live streaming platforms can introduce the local economy and production situation to netizens, recommend excellent local enterprises, and promote sales growth.

Through further analysis, it can be found that the consumer behaviour caused by the above five consumer psychology can be summarised into two types of consumer emotions. Firstly, focus on the consumption patterns of the product. The first type is suitable for shopping consumption, and the second type is suitable for social media consumption. The live broadcast room can provide customers with a more intuitive understanding of the product, which is more three-dimensional than photos. In addition, in e-commerce live streaming, there are usually some special advantages (Tang et al., 2021). After gaining a certain level of attention, customers engaged in thematic discussions around live streaming and conveyed their views on the product, thus forming a requirement for live streaming e-commerce based on social needs. Both consumer psychology focuses on the high cost-effectiveness, degree of thematic discussion, and scope of application of products, both aiming to achieve maximum consumption of the product.

The second focus is on the consumption patterns of live streaming e-commerce targeting anchors (celebrities) or other unexpected events, including ‘fan’ consumption, situational consumption, and emotional consumption. With the emergence of online celebrities and celebrities from various industries, live streaming e-commerce has gradually become a star chasing platform. ‘Fans’ gather on the live streaming platform to pursue stars, and they pay more attention to the stars themselves rather than the products. Contextual consumption focuses on the shopping experience rather than the product itself, while emotional consumption is a consumption behaviour caused by customers’ emotions towards people or events. These three types of consumer psychology focus on people or events, while the proportion of products themselves is relatively small.

When it comes to consumers’ emotional tendencies towards e-commerce live streaming, it can be explained from both positive and negative perspectives. On the positive side, consumers hold a certain favourability towards e-commerce live streaming. For example, live streaming e-commerce provides a new way for consumers to shop comfortably at home, without having to face crowded shopping malls or supermarkets. Live streaming e-commerce can also bring entertainment and interactivity, with many anchors engaging in interesting interactive activities to attract consumers’ attention and increase sales. In addition, consumers can also receive more detailed and intuitive product introductions, and through the actual application demonstration of the anchor, they can more intuitively experience the effectiveness of the product. On the negative side, some consumers still have an emotional tendency of distrust and dissatisfaction towards e-commerce live streaming. For example, false advertising is common, and anchors suspected of selling fake and false advertising also occur from time to time (Hu et al., 2022). In addition, due to the dominant voice of the anchor, some consumers may be misled into purchasing products that do not meet their needs, leading to waste. Some consumers also believe that the live streaming e-commerce process is cumbersome and requires long waiting times, and watching live streaming for a long time can also cause fatigue.

When it comes to identifying the emotional tendencies of consumers on e-commerce live streaming platforms, it is essential to understand their preferences and needs. This study can provide important insights that enable businesses to better understand consumers and their behaviour. By analysing consumers’ emotional tendencies, e-commerce companies can develop more precise marketing strategies to meet their needs, enhance brand image, and enhance brand loyalty.

3 Identification of consumer emotional tendencies

After completing the emotional analysis of consumers, in order to identify their emotional tendencies, relevant emotional tendency data is collected from product reviews in e-commerce live streaming. Based on this data, benchmark words that can represent emotions can be found, such as 'good-looking' in the clothing field as a benchmark word; The term 'good to drink' in the beverage industry can be used as a benchmark term, so it is necessary to choose different benchmark terms for different fields of e-commerce live streaming. However, due to the fact that a single benchmark word cannot fully reflect consumers' emotions, we chose to construct a benchmark word set to replace a single benchmark word.

Assuming the set of e-commerce live product comments is $L = \{l_1, l_2, \ldots, l_n\}$, extract the unigram form of live product comments l_i, which is:

$$unigram = \{unigram_1, unigram_2, ..., unigram_n\} \tag{1}$$

The set of benchmark words for consumers' positive and negative categories is:

$$p\_basewords = \{basewordp_1, basewordp_2, ..., basewordp_n\} \tag{2}$$

$$n\_basewords = \{basewordn_1, basewordn_2, ..., basewordn_n\} \tag{3}$$

The selection criteria for benchmark words are that they appear frequently enough in the average sales of e-commerce live streaming products to represent an analogy (Zhang et al., 2022; Cheng et al., 2022). In order to improve the accuracy of consumer emotional orientation identification, it is necessary to focus on the frequency of $unigram_i$ in the same and opposite corpora. When $unigram_i$ appears more frequently in both corpora, $unigram_i$ cannot be considered as $baseword_i$. Count the number of occurrences of elements in set *unigram*, with the most frequently occurring element being:

$$P(unigram\_most_i) = \frac{M_i}{N_i} \times 100\% \tag{4}$$

In the formula, M_i represents the number of occurrences in the opposite class, and N_i represents the number of occurrences in the same class.

Select a few comment words with smaller $P(unigram\_most_i)$ as reference words to construct a set of reference words. After proposing the *unigram*-form of comments on e-commerce live streaming products, it is necessary to remove the stop words from the comments. However, removing the stop words will still result in more words without emotional tendencies, reducing the efficiency of consumer emotional tendency identification. Therefore, HowNet is used to screen emotional words.

The words in HowNet all have emotional tendencies. If the similarity between the words in the comments on e-commerce live streaming products and the benchmark word set is greater than 0, it indicates that the comment words have emotional tendencies; if the similarity is 0, it indicates that the word does not have an emotional tendency.

By calculating the similarity between the unary words in each comment sentence and the two benchmark word sets *p_baseword* and *n_baseword*, the identification results of emotional tendency unary words can be obtained:

$$l_i = \left(seunigram_1, seunigram_2, ..., seunigram_n\right) \tag{5}$$

In the formula, $seunigram_j$ represents a unary word with emotional tendencies.

If similarity analysis is only conducted through HowNet, it will make it difficult to effectively classify the emotions of some new words, resulting in a decrease in the effectiveness of consumer sentiment identification. Therefore, a combination of HowNet similarity and normalised Google distance (NGD) is used to determine similarity.

Combining HowNet similarity and Google similarity for consumer sentiment orientation recognition has multiple advantages. Firstly, the comprehensive consideration of the conceptual similarity of words and actual language usage has improved accuracy and comprehensiveness. Secondly, it covers rich semantic information and is suitable for emotional analysis needs in different fields and contexts. In addition, by complementing each other, robustness is improved, ensuring the stability and reliability of emotional orientation recognition. Finally, the combination of interpretability and practical application requirements makes the emotional orientation recognition results more understandable. In summary, combining HowNet similarity with Google similarity is a comprehensive, comprehensive, accurate, and interpretable method suitable for various sentiment analysis scenarios.

Calculate the similarity *hn_similarty* between $seunigram_j$ in each live commodity review l_i and the base word set *p_basewords* and the elements in *n_basewords* and HowNet. And in this calculation, it is also necessary to calculate the Google similarity distance of the reference word, so the similarity of HowNet and Google need to be unified processing.

For any $seunigram_j$, the HowNet similarity calculation formula is:

$$p\_similarty = \frac{1}{n}\left(1 - \sum_{i=1}^{n} similarty\left(seunigram_j, basewordp_i\right)\right) \tag{6}$$

$$n\_similarty = \frac{1}{n}\left(1 - \sum_{i=1}^{n} similarty\left(seunigram_j, basewordn_i\right)\right) \tag{7}$$

In the formula, n represents the number of reference word elements.

The final SO-HowNet similarity value for each $seunigram_j$ is:

$$SO - HowNet = p\_similarty - n\_similarty \tag{8}$$

Based on the SO-HowNet similarity value of each $seunigram_j$, the consumer sentiment tendency of $seunigram_j$ calculated through HowNet can be obtained.

By comparing the similarity between $seunigram_j$ in each l_i and the reference word, we can determine the similarity between $seunigram_j$ and the overall emotional category. In order to improve the accuracy of the analysis, we calculate the arithmetic mean value to reflect the average value of the overall emotional orientation. The Google similarity NGD calculation formula for $seunigram_j$ is:

$$SSP\_NGD = \frac{1}{n}\sum_{i=1}^{n} NGD\left(seunigram_j, basewordp_i\right) \tag{9}$$

$$SSN\_NGD = \frac{1}{n}\sum_{i=1}^{n} NGD\left(seunigram_j, basewordn_i\right) \tag{10}$$

According to the above principles, calculate the arithmetic mean value between each $seunigram_j$ and the reference word elements of different categories, so as to reflect the similarity with the whole category.

The weighted average value can reflect the number of times each $seunigram_j$ appears together with the base word, and the more times it appears, the more important $seunigram_j$ is compared to the base word. The calculation formula is as follows:

$$\begin{aligned} JQP\_NGD = &\sum_{i=1}^{n} f\left(seunigram_j, basewordp_i\right) \\ &\cdot NGD\left(seunigram_j, basewordp_i\right) \\ &\cdot\left(\sum_{i=1}^{n} f\left(seunigram_j, basewordp_i\right)\right)^{-1} \end{aligned} \tag{11}$$

$$\begin{aligned} JQN\_NGD = &\sum_{i=1}^{n} f\left(seunigram_j, basewordn_i\right) \\ &\cdot NGD\left(seunigram_j, basewordn_i\right) \\ &\cdot\left(\sum_{i=1}^{n} f\left(seunigram_j, basewordn_i\right)\right)^{-1} \end{aligned} \tag{12}$$

Calculate the NGD values of positive and negative categories by setting normalisation coefficients a and b:

$$END\_PNGD = aSSP\_NGD + bJQP\_NGD \tag{13}$$

$$END\_NNGD = aSSN\_NGD + bJQN\_NGD \tag{14}$$

In the formula, $a + b = 1$.

Based on the above calculation results, calculate SO-NGD according to formula (15) and use it as the final Google similarity distance. The calculation formula is:

$$SO - NGD = END\_PNGD - END\_NNGD \tag{15}$$

After calculating the similarity distance between HowNet and Google, set coefficients α and β to combine the two similarity calculation results, and set $x = \alpha SO - HowNet$ and $y = \beta SO - NGD$. The range of values for SO-HowNet and SO-NGD is between [–1, 1], and the combination of the two is necessary to complete the identification of consumer emotional tendencies. Therefore, x and y must be both greater than 0 or less than 0. Remove the $seunigram_j$ when x and y have different signs, and map the remaining $seunigram_j$ to 2D coordinates. The coordinate mapping results are shown in Figure 1.

If the consumer emotions retained in $seunigram_j$ are denoted as $seunigram\_value_k$, the expression can be written as:

$$seunigram\_value_k = \alpha SO - HowNet + \beta SO - NGD = x + \mathrm{y} \tag{16}$$

In the formula, $k = 1, 2, \ldots, n$.

Calculate each $seunigram_j$ in l_i, retain the emotions of different $seunigram_j$, and calculate consumer emotions:

$$sentence\_value = \sum_{k}^{n} seunigram\_value_k \tag{17}$$

In formula (17), if *sentence_value* < 0 exists, it indicates that the consumer's emotional tendency is positive; On the contrary, as a negative emotional tendency, it completes the identification of consumer emotional tendencies.

Under the 'live streaming+e-commerce' mode, the process of identifying consumer emotional tendencies is shown in Figure 2.

Figure 1 Coordinate mapping diagram

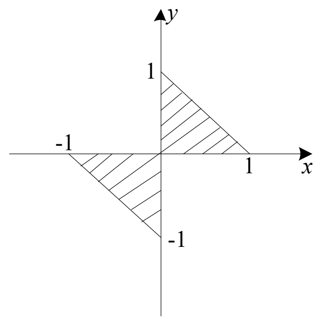
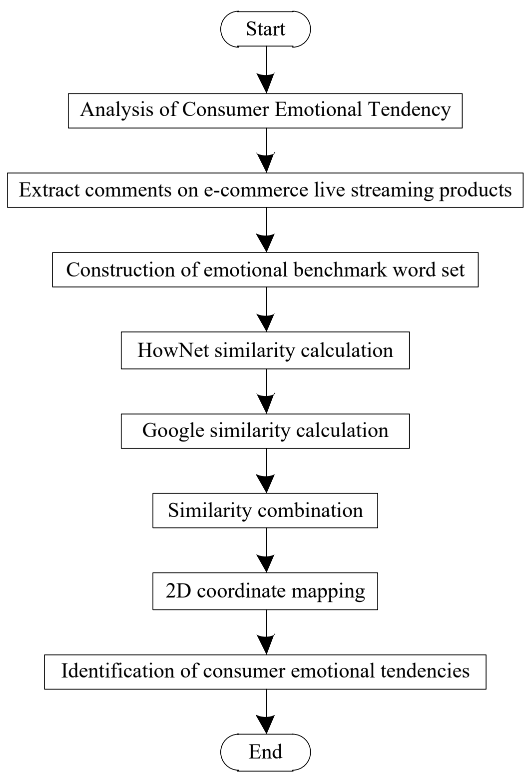


Figure 2 Consumer emotional orientation identification process



4 Experimentation

To verify the effectiveness of the proposed emotional orientation identification method for consumer emotional orientation identification on e-commerce live streaming platforms, comparative validation tests were conducted.

There are a total of 44,640 comments in the comment corpus of the e-commerce live streaming platform for this experiment, and each comment sentence contains emotionally inclined words, that is, positive and negative comments are mixed with each other, with the number of positive and negative words being basically the same. Due to the fact that the comment data on e-commerce live streaming platforms is directly collected, it can be directly used for experimental research without the need for pre-processing.

In order to reduce experimental errors and improve the reliability of experimental results, the method proposed in this paper was compared and validated with the methods in Wang et al. (2021) and Lin et al. (2021) based on the accuracy and identification time of consumer emotional orientation identification.

- Emotional orientation identification accuracy: emotional orientation identification accuracy refers to the percentage of correctly identified emotional orientation results in the total identification results, and the calculation formula is:

$$Precision = \frac{P_c}{P_{all}} \times 100\% \tag{18}$$

  In the formula, P_{all} represents the total emotional orientation identification result, and P_c represents the correctly identified emotional orientation result.

- Emotional tendency identification time: emotional tendency identification time refers to the time range for analysing consumers' emotional tendencies, and the shorter the time, the higher the identification efficiency.

4.1 Accuracy results of consumer emotional orientation identification

The accuracy results of the three methods for identifying consumer emotional tendencies are shown in Table 1.

From the accuracy results of consumer sentiment orientation identification shown in Table 1, it can be seen that with multiple experiments conducted, there are significant differences in the accuracy results of the three methods. Among them, the identification accuracy of the method in this paper always remains above 90%, while the highest identification accuracy of the methods in Wang et al. (2021) and Lin et al. (2021) did not reach 90%. Therefore, it indicates that this method can more accurately identify the emotional tendencies of consumers on e-commerce live streaming platforms.

4.2 Identification time of consumer emotional tendencies

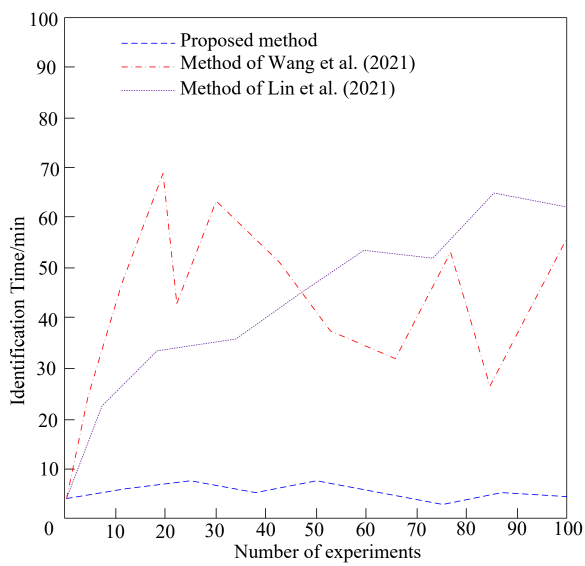
The time results of consumer sentiment orientation identification using the three methods under the same environment and data are shown in Figure 3.

Observing Figure 3, it can be seen that under the same experimental conditions, compared with the two literature methods, the method proposed in this paper significantly reduces the identification time of consumer emotional tendencies, with a maximum of no more than ten minutes and a smaller fluctuation range. The identification time results of the methods in Wang et al. (2021) and Lin et al. (2021) not only fluctuate significantly, but also have an overall identification time of over 60 minutes. Therefore, it indicates that the method proposed in this article can effectively shorten the identification time of consumer emotional tendencies.

Table 1 Accuracy of consumer emotional orientation identification

Number of experiments	*Accuracy/%*		
	Wang et al. (2021) method	*Lin et al. (2021) method*	*Proposed method*
10	70	82	92
20	71	76	93
30	75	81	90
40	68	73	97
50	72	75	94
60	78	71	98
70	65	70	95
80	82	73	91
90	75	80	97
100	70	72	90

Figure 3 Identification time results (see online version for colours)



5 Conclusions

In order to accurately and quickly identify the emotional tendencies of consumers on e-commerce platforms, a method for identifying consumer emotional tendencies under the ‘live streaming+e-commerce’ mode is proposed. The performance of the method was verified from both theoretical and experimental perspectives. This method has high identification accuracy and short identification time when identifying consumer emotional tendencies. Compared with the method based on the key causal connection of transfer entropy, the accuracy of emotional orientation identification in this method is always at 90%; compared with the method based on multitask learning, the emotional orientation identification time of this method does not exceed ten minutes. Therefore, it indicates that the method proposed in this article can improve the performance of consumer sentiment orientation identification.

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