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# An affective algorithm-based approach to user emotion recognition in digital persuasive design

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**Abstract** Based on the theory of persuasion, this paper analyzes the application of persuasive design on products. It constructs a product emotion modeling database and optimizes the construction of product design model by combining orthogonal design method. The improved SO-PMI algorithm is proposed, and the SO-PMI algorithm is extended to enhance the emotion recognition ability in Chinese context. Adopt stratified sampling and domain equalization strategy for systematic collection, and construct a hybrid emotion corpus covering 2 domains. For the electronics dataset, the model in this paper gains improvement in precision, recall, and F1 value metrics, which are 0.6693, 0.7011, and 0.6848, respectively.For the home furnishing kitchen and bathroom dataset, the model in this paper also achieves the best performance. The proposed model demonstrates significant advantages on all three sentiment categories of the electronics dataset. The accuracy of 99% is achieved in the Home Kitchen and Bath dataset, which is 12.6% better than the original model.

**Index Terms** persuasive design, orthogonal design, SO-PMI algorithm, sentiment recognition

## I. Introduction

Today's market competition has been upgraded from traditional hardware services to content services, from product competition to service system competition, and its business logic is undergoing a great change [1], [2]. The traditional design services from the consistency of the standard to the thousands of personalized customization, the research object from the tangible carrier to the intangible behavior, the focus of the work from the physical logic converted to the operational logic [3]-[5]. How users' cognition is influenced, how behaviors are designed, and how design can bring good business value and social innovation are all topics about behavioral change that deserve to be explored in depth.

The Internet, big data and artificial intelligence have provided users with a convenient life, but they have also caused social fragmentation, of which the most influential is the information cocooning effect [6], [7]. Persuasive design is based on the background of information cocooning, and proposes a persuasive strategy to change users' cognition and behavior [8]. Persuasive design comes from persuasion technology, which is a research direction established based on multidisciplinary theories such as psychology and computer science [9], [10]. Its purpose is to inspire design thinking by researching and analyzing user behavior, and to establish design methods that can effectively guide and transform user behavior [11]-[13]. By focusing on users' attitudes and behaviors to achieve interaction design, it provides strong theoretical support and practical guidance for product development, service strategy and social innovation [14]-[16]. Due to the practical nature of persuasive itself and the intersectionality of disciplines, a systematic methodological system and a unified theoretical standard for human emotions in persuasive design has not yet been established, and further research must be carried out.

This paper firstly starts from the analysis of persuasion object-behavior and its related concepts, and explores the timing of the emergence of behavioral influences and triggers. The idea of constructing a product emotion modeling database is proposed to improve the traditional product design process using orthogonal design. The SO-PMI algorithm for constructing a domain emotion dictionary is introduced, and an extended SO-PMI algorithm is designed to address the problem of possible data sparsity. A mixed sentiment corpus containing the domains of electronic products and home decoration and kitchen and bath is collected to construct a product sentiment database. Cross-domain experiments are conducted to verify the significant advantages of the proposed method in terms of precision rate, recall rate and F1 value.

## II. Digital persuasive design based on emotional algorithms

In the context of the deep integration of digital technology and user experience, persuasive design improves user engagement through behavioral intervention strategies, the core of which lies in accurately identifying the user's emotional state to achieve personalized interaction. However, the scarcity and domain specificity of product emotion data constrain the generalization ability of emotion models, and traditional emotion algorithms are susceptible to the influence of data sparsity in the Chinese context, which leads to the bias of emotion tendency determination. In this paper, we conduct a systematic research on the user emotion recognition method, and propose a three-dimensional solution that integrates multi-source data collection, domain-adaptive emotion dictionary construction and improved emotion algorithm.

## *II. A.Behavioral analysis based on persuasion theory*

### II. A. 1) Behavioral influences analysis

In this paper, the influencing factors of behavior are divided into two perspectives of external environment and internal factors to be analyzed, and the specific influencing mechanism is shown in Figure 1. Among them, the extrinsic environment is viewed in conjunction with the product, and its influencing factors include the social and cultural background and the product environment. Among the intrinsic factors, physiological factors and psychological factors are put together because of their cross-cutting and mutual influence, and are mainly included in the three levels of body perception, psychological influence and emotional resonance.

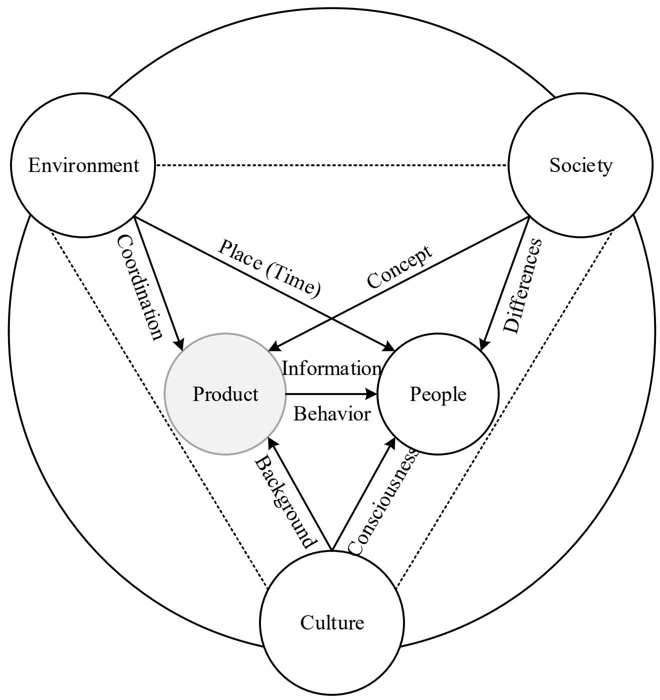


Figure 1: Influence Mechanism

### II. A. 2) Timing of triggers

Combined with the user's motivation and ability in the behavioral model, the timing of the appearance of trigger factors can be divided into the following four types.

Accidental type: It refers to the trigger factors appearing randomly in the user's behavioral process and usage scenario, and their appearances generally have no fixed rules and are set by the persuasion implementers according to their own purposes.

Event-based: It refers to the fact that the triggering factor is bound to a specific event, such as recommending The Avengers to the user at the end of the video page after watching the movie Captain America.

Cyclic: The system displays triggers according to a strict cyclical pattern. For example, the bedtime function of iOS comes with an alarm clock, which pushes reminders to users at regular intervals every day according to the bedtime and wake-up time set by the users themselves.

Precision: Triggers appear in a resourceful and precise way, by accurately grasping the user's current motivation and ability, and releasing triggers at the right time. For example, Mobile Taobao accurately predicts the commodities that users are interested in through their shopping records or browsing behavior paths, thus accurately generating personalized recommendations for users on the home page. For example, if a user has been browsing a lot of baby products recently, other baby products will be recommended for the user on the home page, including the banner.

### II. B. Product Emotional Modeling Database

#### II. B. 1) Methods of obtaining product samples

The key step in constructing a product emotion modeling database is to obtain product modeling samples. At present, the main collection method of product modeling samples consists of manual and data mining, as shown in Figure 2. One of the common ways is the collection of field research literature and other content and the form of network data mining, the main workflow of these ways is basically the same as the acquisition of emotional vocabulary. At present, a large number of studies have been able to effectively use artificial intelligence technology to assist the development of product design, however, in order to improve the quality of the design, the relevant research needs a large number of sample data, on the one hand, in terms of efficiency, the traditional collection of samples can not be efficiently complete the task, on the other hand, in terms of the number, the product as an artifact, the number of its shape is far less than the number of natural objects, when faced with the type of products, the number of products, the sample size plummeted. On the other hand, in terms of quantity, products as artifacts have far fewer shapes than natural objects, and when faced with fewer types and quantities of products, the sample size plummets, which in turn directly affects the stability of the training model and the accuracy of the research conclusion. Some researchers suggest that the product database can be expanded from an “open source” perspective by increasing the sample types and numbers based on existing products through designers' or users' drawings, as well as algorithms or software generation.

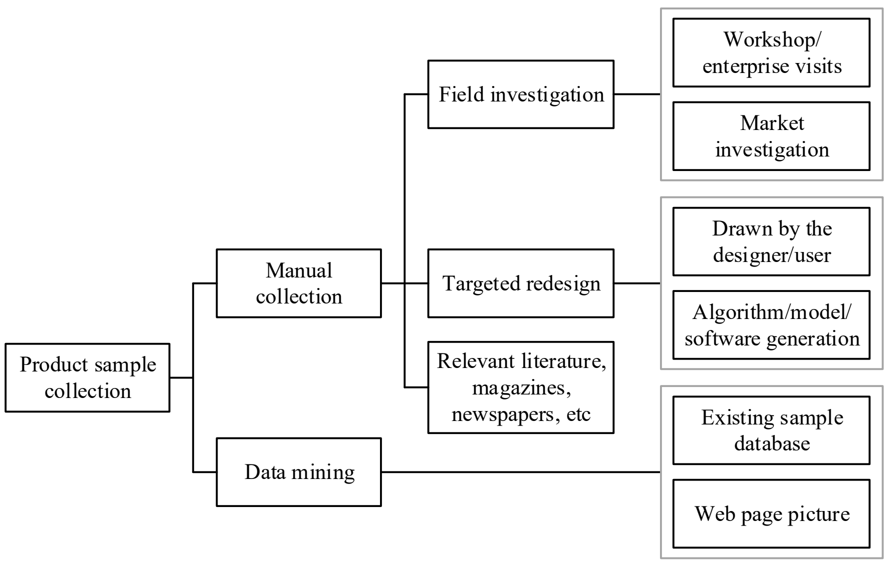


Figure 2: Main collection methods of product samples

#### II. B. 2) Construction of product emotional modeling database based on orthogonal design

In research related to perceptual engineering and product design, exploring the correlation between product styling with different combinations of morphological elements and users' emotional preferences is a key point of research. However, even for a single product category, the number of different shapes is diverse, which, together with the diversity of design factors such as functional attributes, colors, materials, and textures, makes the research scale large, costly, and often difficult to implement due to the non-regular limitation of the mutual constraints among design factors. Orthogonal design is a research method that can effectively deal with multi-attribute problems, which can help researchers to reduce redundancy, select representative attributes to form a persuasive combination of experiments, and aim to improve product quality and target research efficiency by replacing full-scale experiments with partial experiments. Orthogonal design has been introduced into product design to guide the robust design and development of new products, and is now widely used in the product field to provide researchers with highly generalized virtual product design combinations, taking into account all the factors and attributes, to achieve the optimal combination of design quality, cost, and research efficiency.

### II. C. Construction of the domain sentiment lexicon

#### II. C. 1) SO-PMI algorithm

The Point Mutual Information Algorithm (PMI) determines the emotional tendency of two words by judging the degree of association between them. If the correlation degree is higher, the more likely that the two words have the same emotional tendency. That is, if the probability of the word to be selected appearing together with a positive sentiment word is higher than the probability of the word appearing with a negative sentiment word, then the sentiment tendency of the word to be selected is considered to be positive.The PMI formula is as follows:

$$PMI(word_1, word_2) = \log_2\left(\frac{P(word_1 \,\&\, word_2)}{P(word_1)P(word_2)}\right) \tag{1}$$

where $P(word_1 \,\&\, word_2)$ represents the probability of $word_1, word_2$ in the same text. $P(word_1)$ is the probability of $word_1$, occurring alone, i.e., the ratio of the text containing $word_1$, to the total text. $P(word_2)$ is the probability of $word_2$ appearing alone. According to the formula, there are three possibilities for $PMI(word_1, word_2)$. $PMI(word_1, word_2) > 0$, that is, the probability of $word_1, word_2$ occurring at the same time is greater than the probability of occurring separately, indicating that $word_1, word_2$ is correlated, and the greater the value of $PMI(word_1, word_2)$, The higher the correlation between the two words; $PMI(word_1, word_2) = 0$, that is, there is no case in the corpus that contains $word_1, word_2$, which means that there is no association between the two words. $PMI(word_1, word_2) < 0$ means $word_1, word_2$ are mutually exclusive.

Assuming that the total number of text entries in the corpus is N, $n_{word_1}$ represents the number of texts in the corpus that contain $word_1$, , then the formula for $P(word_1)$ is:

$$P(word_1) = \frac{n_{word1}}{N} \tag{2}$$

Similarly, the probability $P(word_1, word_2)$ of occurrence of a text containing both $word_1, word_2$ is given by:

$$P(word_1, word_2) = \frac{n_{word1,word2}}{N} \tag{3}$$

By calculating $PMI(word_1, word_2)$ in (1), the similarity of $word_1, word_2$ can be derived. Similarly, the similarity between the word to be selected and all the baseline sentiment words can be derived by this method, which is the Point Mutual Information algorithm for Sentiment Propensity, SO-PMI.The formula for SO-PMI is as follows:

$$SO(word_1) = PMI(word_1, PSemantics) - PMI(word_1, NSemantics) \tag{4}$$

The idea of SO-PMI algorithm is to find out the affective tendency of the word $word_1$, by calculating the difference of the PMI index between the word $word_1$, of unknown affective tendency and the positive and negative benchmark words. The positive and negative benchmark phrases are denoted by PSemantics and NSemantics, respectively.

Let a certain positive affective word of PSemantics be $p$, then the PMI formula for the unknown word $word_1$, with $p$ is:

$$PMI(word_1, ps) = \log_2\left(\frac{P(word_1 \,\&\, ps)}{P(word_1)P(ps)}\right) \tag{5}$$

where $P(word_1 \,\&\, ps)$ is the probability that $word_1$, occurs in the same text with the positive sentiment word $ps$. $P(word_1)P(ps)$ represents the probability that $word_1$, and $ps$ occur in the text alone, respectively. On this basis, the PMI values of $word_1$, and all the positive emotion words in PSemantics are calculated separately and summed up, and the total correlation between $word_1$, and positive emotion words can be obtained. That is, the pointwise mutual information between $word_1$, and PSemantics is given by the following formula:

$$PMI(word_1, Psemantics) = \sum_{ps \in Psemantics}^{ps} PMI(word_1, ps) \tag{6}$$

Similarly, the pointwise mutual information of $word_1$, with the negative benchmark phrase Nsemantics can be derived, and the value of SOPMI for $word_1$, can be obtained by subtracting $PMl(word_1, Psemantics)$ from $PMI(word_1, Nsemantics)$, which is calculated as follows:

$$SOPMI(word_1) = \sum_{ps \in Psemantics}^{ps} PMI(word_1 ps) \cdot \sum_{ns \in Nsemantics}^{ns} PMI(word_1, ns) \tag{7}$$

There are three possibilities for the SOPMI value derived from the above formula. When $SOPMI(word_1) > 0$, i.e., $word_1$, is more likely to co-occur with positive affective words than with negative affective words, the word can be considered as a positive affective word; when $SOPMI(word_1) = 0$, it means that the word is neutral; and when $SOPMI(word_1) < 0$, it is considered as a negative affective word.

#### II. C. 2) Domain Sentiment Dictionary Construction Based on Extended SO-PMI

Using the SO-PMI algorithm, the unknown words can be automatically labeled with sentiment, compared with the manual labeling method, the method greatly reduces the time spent on constructing the sentiment dictionary, and has a good accuracy rate. At present, this algorithm has a relatively wide range of applications in the field of text sentiment recognition. However, the algorithm is not 100% applicable to the Chinese context, the Chinese language is profound and a kind of emotion may have a variety of ways of expression. In some extreme conditions, the frequency of certain words with test is very low, or the probability of its co-occurrence in the emotion benchmark word is very low, or even 0, which leads to the SO-PMI value of emotion words tends to be close to 0, and thus judged as neutral words, but these words largely contain emotional tendency, which is the sparse data problem. For this reason the problem of data sparsity can be improved by extending the SO-PMI algorithm.

The SO-PMI algorithm realizes the candidate word sentiment polarity judgment by calculating the correlation between the candidate word and the sentiment benchmark word. The extended SO-PMI algorithm can improve the sentiment recognition of sparse data by expanding the form of sentiment benchmark words. The idea is to improve the matching possibility by introducing synonyms of the sentiment benchmark words. In this paper, in the process of creating the domain sentiment dictionary, the calculation of the SO-PMI value of the original word to be matched with the sentiment benchmark word is changed to the calculation of the synonym of the word to be matched with the sentiment benchmark word in the word, and finally, the words with recognized sentiment tendency are placed into the domain dictionary.

## III. Analysis of the effectiveness of affective algorithms

The product review dataset constructed in this paper is systematically collected using stratified sampling and domain equalization strategies. The data sources cover the product review modules of two major e-commerce platforms, Jingdong and Taobao, during the period from January 2024 to June 2024, with a focus on electronic products and home furnishing and kitchen and bathroom categories to ensure that the dataset is representative of the industry. After data cleaning, 12,568 valid comments are retained, and a hybrid sentiment corpus covering 2 domains is constructed.

### *III. A. Construction of an Emotion Database*

#### III. A. 1) Keyword acquisition

Keywords can point out the relevant connections in the text of positive and negative product sentiment, and can quickly collect information from a large number of reviews, so the first step in the analysis of this paper is to obtain keywords. After using Python to perform Chinese segmentation on the two texts, the words that are not very relevant to the study of this paper are filtered out, and the 1000 words with the highest document frequency in the segmentation results are selected as keywords. Document frequency refers to the frequency of keywords appearing in the text of image reviews. The positive and negative sentiment comment text of the product comment text will be organized separately to get the positive sentiment text and negative sentiment text. The emotional keywords in the review text are shown in Table 1, and the most frequent word in the positive review text is “good”, with a word frequency of 8927, while the most frequent word in the negative review text is “general”, with a document frequency of 992.

Table 1: Emotional Keywords in the positive comment text section

| Positive text keywords | | | Negative text keywords | | |
|---|---|---|---|---|---|
| Label word | Word frequency | Document frequency | Label word | Word frequency | Document frequency |
| Not bad | 8927 | 8901 | General | 1085 | 992 |
| Worth | 8286 | 8244 | Poor quality | 936 | 893 |
| Good | 7834 | 7802 | Useless | 882 | 801 |
| Cultural | 7225 | 7133 | Dirty | 725 | 643 |
| Beautiful | 6709 | 6625 | Ugly | 611 | 522 |
| Devoted | 5425 | 5321 | Of trouble | 482 | 454 |
| Cute | 4113 | 4044 | Chaotic | 371 | 352 |
| Useful | 3275 | 3106 | Wasteful | 294 | 271 |
| Elegant | 2011 | 1942 | Bad | 208 | 194 |

| | | | | | |
|---|---|---|---|---|---|
| Worth buying | 1388 | 1297 | Boring | 186 | 173 |

**III. A. 2) Constructing the keyword correlation matrix**

In co-occurrence analysis, high-frequency words are hardly an objective reflection of the correlations between words; they are only absolute values of co-occurrence frequency. Directly using the raw count values in the co-occurrence matrix may be affected by high-frequency words because they may co-occur in many documents. The raw matrix must be inclusionized to construct the correlation matrix. By using the correlation matrix, you can better measure the relative strength between keywords because it is normalized by considering the frequency of occurrence of each keyword. In this paper, the Ochiai coefficient formula is used for the process to convert the values occurring in the covariance matrix into a correlation matrix. The product positive emotion keyword correlation matrix and negative emotion keyword correlation matrix are shown in Table 2 and Table 3, respectively. It can be seen that the correlation coefficient of the keyword "nice" is 1. The correlation coefficient of the keywords "pretty" and "nice" is 0.099. The value of each cell in the correlation matrix reflects the distance between the two high-frequency words. The value of each cell in the correlation matrix reflects the distance between two high-frequency words: the larger the value, the higher the degree of correlation; the smaller the value, the lower the degree of correlation. The value on the main diagonal is always 1, indicating the degree of relevance of each high-frequency word to itself. Therefore, the distance between the keywords "pretty" and "nice" is relatively small.

Table 2: Correlation Matrix of Positive Emotional Keywords

| | Not bad | Worth | Good | Cultural | Beautiful | Devoted | Cute | Useful | Elegant | Worth buying |
|---|---|---|---|---|---|---|---|---|---|---|
| Not bad | 1 | 0.348 | 0.281 | 0.303 | 0.099 | 0.214 | 0.308 | 0.277 | 0.195 | 0.208 |
| Worth | 0.348 | 1 | 0.199 | 0.232 | 0.201 | 0.308 | 0.222 | 0.401 | 0.285 | 0.303 |
| Good | 0.281 | 0.199 | 1 | 0.182 | 0.228 | 0.325 | 0.147 | 0.396 | 0.028 | 0.149 |
| Cultural | 0.303 | 0.232 | 0.182 | 1 | 0.329 | 0.128 | 0.099 | 0.201 | 0.033 | 0.386 |
| Beautiful | 0.099 | 0.201 | 0.228 | 0.329 | 1 | 0.426 | 0.175 | 0.284 | 0.098 | 0.333 |
| Devoted | 0.214 | 0.308 | 0.325 | 0.128 | 0.426 | 1 | 0.276 | 0.281 | 0.219 | 0.406 |
| Cute | 0.308 | 0.222 | 0.147 | 0.099 | 0.175 | 0.276 | 1 | 0.281 | 0.103 | 0.383 |
| Useful | 0.277 | 0.401 | 0.396 | 0.201 | 0.284 | 0.281 | 0.281 | 1 | 0.227 | 0.275 |
| Elegant | 0.195 | 0.285 | 0.028 | 0.033 | 0.098 | 0.219 | 0.103 | 0.227 | 1 | 0.183 |
| Worth buying | 0.208 | 0.303 | 0.149 | 0.386 | 0.333 | 0.406 | 0.383 | 0.275 | 0.183 | 1 |

Table 3: Correlation Matrix of Negative Emotional Keywords

| | General | Poor quality | Useless | Dirty | Ugly | Of trouble | Chaotic | Wasteful | Bad | Boring |
|---|---|---|---|---|---|---|---|---|---|---|
| General | 1 | 0.308 | 0.221 | 0.418 | 0.333 | 0.281 | 0.093 | 0.099 | 0.103 | 0.221 |
| Poor quality | 0.308 | 1 | 0.293 | 0.104 | 0.095 | 0.109 | 0.226 | 0.331 | 0.278 | 0.095 |
| Useless | 0.221 | 0.293 | 1 | 0.298 | 0.246 | 0.332 | 0.198 | 0.234 | 0.321 | 0.428 |
| Dirty | 0.418 | 0.104 | 0.298 | 1 | 0.339 | 0.255 | 0.142 | 0.309 | 0.268 | 0.204 |
| Ugly | 0.333 | 0.095 | 0.246 | 0.339 | 1 | 0.231 | 0.222 | 0.098 | 0.107 | 0.203 |
| Of trouble | 0.281 | 0.109 | 0.332 | 0.255 | 0.231 | 1 | 0.417 | 0.502 | 0.193 | 0.178 |
| Chaotic | 0.093 | 0.226 | 0.198 | 0.142 | 0.222 | 0.417 | 1 | 0.602 | 0.095 | 0.111 |
| Wasteful | 0.099 | 0.331 | 0.234 | 0.309 | 0.098 | 0.502 | 0.602 | 1 | 0.342 | 0.203 |
| Bad | 0.103 | 0.278 | 0.321 | 0.268 | 0.107 | 0.193 | 0.095 | 0.342 | 1 | 0.178 |
| Boring | 0.221 | 0.095 | 0.428 | 0.204 | 0.203 | 0.178 | 0.111 | 0.203 | 0.178 | 1 |

***III. B. Extended SO-PMI validation of effectiveness***

**III. B. 1) Comparison methods and evaluation indicators**

TextCNN, BERT, PMI, and SO-PMI are used as benchmark methods:.

(1) TexCNN: Based on pre-trained word embedding vectors after convolutional pooling to predict sentiment tendency, the model structure is simple and runs fast.

(2) BERT: Using the advantage that BERT model can get the deep semantic information of text context, the text is input into the model to get the 512-dimensional word vectors of each word, and then the word feature vectors containing deep semantic information are obtained through the 8-layer transformer encoder structure.

(3) PMI: the original model, which judges the emotional tendency of two words by judging the correlation between them.

(4) SO-PMI: Improve the PMI model to find out the affective tendency of word $word_1$, by calculating the difference between the PMI index of word $word_1$, with unknown affective tendency and the positive and negative benchmark words.

In order to ensure the accuracy of the model metrics and better reflect the real performance of the model, the macro-averaged precision rate P, recall rate R, and F1 value are used as evaluation indexes. The calculation formula is as follows:

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

$$Recall = \frac{TP}{TP+FN} \tag{9}$$

$$\mathrm{F1} = \frac{2\times \mathrm{Precision}\times \mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}} \tag{10}$$

$$P_{macro} = \frac{1}{n}(\sum_{i=1}^{n} P_i) \tag{11}$$

$$R_{macro} = \frac{1}{n}(\sum_{i=1}^{n} R_i) \tag{12}$$

$$F1_{macro} = \frac{1}{n}(\sum_{i=1}^{n} F1_i) \tag{13}$$

where TP denotes a sample that is actually positive and the model prediction result is also positive, FP denotes a sample that is actually negative and the model prediction result is positive, TN denotes a sample that is actually negative and the model prediction result is also negative, and FN denotes a sample that is actually positive and the model prediction result is negative. In multi-label classification the label of interest is considered as a positive sample and the rest of the labels form a negative sample. For example, the positive affective label FP denotes a sample where the predicted outcome is positive but the actual label is neutral or negative.

#### III. B. 2) Model comparison results

A comparison of the experimental results on the two types of datasets is shown in Table 4. For the electronics dataset, compared with SO-PMI based, this paper improves sentiment recognition for sparse data by expanding the form of sentiment benchmark words, which makes the algorithm more suitable for Chinese context. The precision, recall, and F1 value metrics are improved to 0.6693, 0.7011, and 0.6848, respectively.For the home furnishing kitchen and bathroom dataset, the model in this paper also achieves the best performance. The precision, recall, and F1 value are improved by 4.61%, 2.72%, and 3.69% respectively compared to the original model PMI.

Table 4: Comparison of Experimental Results

| Data set | Model | P | R | F1 |
|---|---|---|---|---|
| Electronic products | TextCNN | 0.4926 | 0.5267 | 0.5091 |
| | BERT | 0.5931 | 0.6022 | 0.5976 |
| | PMI | 0.6126 | 0.6344 | 0.6233 |
| | SO-PMI | 0.6552 | 0.6803 | 0.6675 |
| | The proposed | 0.6693 | 0.7011 | 0.6848 |
| Home decoration of kitchen and bathroom | TextCNN | 0.6372 | 0.6535 | 0.6452 |
| | BERT | 0.6442 | 0.6603 | 0.6522 |
| | PMI | 0.6551 | 0.6832 | 0.6689 |
| | SO-PMI | 0.6874 | 0.6995 | 0.6934 |
| | The proposed | 0.7012 | 0.7104 | 0.7058 |

### III. B. 3) Confusion Matrix Comparison Results

The confusion matrix of the electronics dataset on each model is shown in Table 5. The proposed model shows significant advantages on all three emotion categories. For positive emotions, it reaches 270 cases of true positives, which is an improvement of 5 cases over the suboptimal model SO-PMI, indicating that the model has a stronger sensitivity to recognize positive emotions. In neutral emotion classification, the model outperforms all comparison methods with 45 true positives, while keeping false positives at 10 cases. For negative emotions, the model improves 9.7% accuracy compared to the suboptimal model SO-PMI.

Table 5: Confusion Matrix of Electronic Product Dataset

| Data set | Model | | | Predictive label | | |
|---|---|---|---|---|---|---|
| | | | | Positive | Neutral | Negative |
| Electronic products | TextCNN | True label | Positive | 264 | 0 | 16 |
| | | | Neutral | 17 | 35 | 3 |
| | | | Negative | 73 | 0 | 92 |
| | BERT | | Positive | 258 | 2 | 20 |
| | | | Neutral | 12 | 43 | 0 |
| | | | Negative | 55 | 6 | 104 |
| | PMI | | Positive | 261 | 19 | 0 |
| | | | Neutral | 14 | 41 | 0 |
| | | | Negative | 41 | 11 | 113 |
| | SO-PMI | | Positive | 265 | 0 | 15 |
| | | | Neutral | 13 | 42 | 0 |
| | | | Negative | 33 | 0 | 132 |
| | The proposed | | Positive | 270 | 10 | 0 |
| | | | Neutral | 10 | 45 | 0 |
| | | | Negative | 17 | 0 | 148 |

The confusion matrix of the home kitchen and bathroom dataset on each model is shown in Table 6. The accuracy of the proposed model reaches 99%, which is much higher than the 82.4% accuracy of the TextCNN model and 12.6% higher than the original model, and it has a greater advantage than the SO-PMI model in the recognition of positive emotions.

Table 6: Confusion Matrix of Home Decoration Kitchen and Bathroom Dataset

| Data set | Model | | | Predictive label | | |
|---|---|---|---|---|---|---|
| | | | | Positive | Neutral | Negative |
| Home decoration of kitchen and bathroom | TextCNN | True label | Positive | 255 | 33 | 12 |
| | | | Neutral | 14 | 36 | 0 |
| | | | Negative | 19 | 10 | 121 |
| | BERT | | Positive | 264 | 33 | 3 |
| | | | Neutral | 12 | 38 | 0 |
| | | | Negative | 25 | 2 | 123 |
| | PMI | | Positive | 259 | 32 | 9 |
| | | | Neutral | 9 | 41 | 0 |
| | | | Negative | 9 | 9 | 132 |
| | SO-PMI | | Positive | 286 | 14 | 0 |
| | | | Neutral | 5 | 45 | 0 |
| | | | Negative | 0 | 0 | 150 |
| | The proposed | | Positive | 297 | 3 | 0 |
| | | | Neutral | 2 | 48 | 0 |
| | | | Negative | 0 | 0 | 150 |

Cross-dataset analysis shows that the proposed model makes breakthroughs in both sentiment discrimination accuracy and classification stability.

## IV. Conclusion

In this paper, for the digital persuasive design of products, we design a user emotion recognition method based on emotion algorithm, and set up corresponding experiments to verify the effectiveness of the scheme.

For the electronic product dataset, this paper's model obtains an improvement in the precision rate, recall rate, and F1 value indexes, which are 0.6693, 0.7011, and 0.6848, respectively.For the home furnishing kitchen and bathroom dataset, this paper's model also achieves the best performance. Precision, recall, and F1 value are improved by 4.61%, 2.72%, and 3.69% respectively compared to the original model PMI.

The proposed model demonstrates significant advantages on all three sentiment categories of the e-product dataset. For positive emotions, its true positives reach 270 cases, which is an improvement of 5 cases over the suboptimal model SO-PMI, indicating that the model has a stronger sensitivity to recognize positive emotions. In neutral emotion classification, the model outperforms all comparison methods with 45 true positives, while keeping false positives at 10 cases. For negative emotions, the model improves the accuracy by 9.7% compared to the suboptimal model SO-PMI. The proposed model achieves 99% accuracy in the home furnishing kitchen and bathroom dataset, which is much higher than the 82.4% accuracy of the TextCNN model, and improves 12.6% over the original model, and has a large advantage over the SO-PMI model in recognizing positive emotions.

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