Construction and Validation of a Fine-Grained Sentiment and Attitude Lexicon

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Abstract

For governments and enterprises, traditional positive-negative sentiment binary classification can no longer meet practical demands when facing frequently occurring and widely influential information events; more precise and in-depth analytical tools are required. To address the issues of coarse granularity and low keyword coverage in existing sentiment dictionaries, this paper expands evaluative emotions based on cognitive-appraisal theory, crawls hot events from social media to form a corpus, and has experts screen and categorize on the basis of existing dictionaries, ultimately forming a fine-grained sentiment attitude dictionary containing 50 emotion categories. The accuracy and effectiveness of the dictionary in recognition are then tested through a combination of manual evaluation and event analysis methods. First, using manual classification as the reference standard, the dictionary achieved a mean accuracy of 88% for emotion categories, demonstrating its ability to accurately identify fine-grained emotions. Second, after conducting text analysis on the "Haitian Soy Sauce Double Standards Incident" and the "Chengdu Girl Bitten Incident" using the dictionary, it was found that the broad-category emotion recognition results aligned with the overall public tendencies, and heterogeneity in temporal changes of fine-grained emotions was also observed, providing support for the effectiveness of fine-grained sentiment analysis in coping with and understanding complex public opinion environments.

Full Text

Preamble

Construction and Validation of a Fine-Grained Emotional Attitude Lexicon

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Abstract: For governments and enterprises facing frequent and widely impactful information incidents, traditional binary positive-negative sentiment identification no longer meets practical needs; more precise and in-depth analytical tools are required. To address the problems of coarse granularity and low keyword coverage in existing sentiment lexicons, this paper expands evaluative emotions based on cognitive-appraisal theory, crawls hot events from social media to form a corpus, and has experts screen and categorize keywords on the basis of existing dictionaries. The result is a fine-grained emotional attitude lexicon comprising 50 emotion categories. We then tested the lexicon' s accuracy and effectiveness in identification through both manual evaluation and event analysis. First, using manual classification as the reference standard, the lexicon achieved an average accuracy of 88% for emotion categories, demonstrating its ability to accurately identify nuanced emotions. Second, applying the lexicon to analyze texts from the "Haitian Soy Sauce Double-Standard Incident" and the "Chengdu Girl Bitten by Dog Incident" revealed that the broad-category sentiment identification results aligned with overall public tendencies, while also revealing heterogeneity in the temporal changes of fine-grained emotions. These findings support the effectiveness of fine-grained sentiment analysis in responding to and understanding complex public opinion environments.

Keywords: Fine-grained identification; Social media corpus; Sentiment analysis; Sentiment lexicon; Online public opinion

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In today' s era of rapid internet development, social media has become the core channel for citizens to obtain information, express opinions, and participate in public discussion. According to the 53rd "Statistical Report on China' s Internet Development," by December 2023, China' s internet user population had reached 1.092 billion [1]. News organizations, enterprises, and government departments have established official accounts on social media platforms such as Weibo to release policy announcements, interact with the public, and obtain feedback. By December 2023, all 31 provinces (autonomous regions and municipalities) had opened government Weibo accounts, with over 100,000 government agency Weibo accounts certified on the Sina platform. Social media is not only a platform for information dissemination but has also become the origin and amplifier of information incidents. From the 2012 Diaoyu Islands dispute and the Sanlu "toxic milk powder" scandal to Xin Jifei' s stigmatization of food additives as "technology and hardcore technology" and the Chengdu No. 49 Middle School incident [2], these events originated on social media, quickly attracted massive attention, spread rapidly, and even triggered offline collective incidents, causing enormous losses to enterprises and relevant government departments, sometimes leading to business closures [3]. In light of this, to avoid the malignant development of public opinion, governments and enterprises need to closely monitor citizens' attitudes in information incidents, focusing not only on the valence of emotions but also deeply exploring the subtle differences and changing trends in emotions to formulate appropriate response measures and resolve contradictions and conflicts [4].

One key technology for understanding citizens' attitudes is sentiment analysis. This is partly because emotions play an important role in the dissemination and development of information incidents. For example, netizens in an angry state are more willing to forward information, leading to faster and wider information diffusion [5, 6]. Some researchers have categorized group incidents into organized, self-organized, and emotion-dominated types based on the psychological states of individuals within groups, with emotion-dominated group incidents characterized by suddenness, extreme destructiveness, and susceptibility to exploitation [7]. When a group is controlled by a certain emotion, individuals within it are easily provoked to engage in intense behaviors [8]. Additionally, when organizations or individuals respond to groups, they need to adjust their strategies based on emotion types [9]. Therefore, developing tools that accurately identify public emotions is essential.

In sentiment analysis, text information from social media, such as posts and comments, has become an important information source due to its high coverage, timeliness, and authenticity. First, China' s internet penetration rate has reached 77.5% [1]. More citizens choose to obtain the latest information through social media rather than newspapers or television. Social media has broken geographical restrictions and lowered the threshold for publishing, allowing anyone to express their views and opinions and participate in discussions. Therefore, social media text sources are more extensive and can comprehensively reflect public opinion compared to traditional public opinion surveys. Second, social media is a real-time, interactive, and open platform where people can check news and express opinions anytime on mobile phones or computers. This information influences other netizens' attitudes and behaviors, and as the number of followers increases, the direction of public opinion continuously changes [10]. Only by analyzing social media texts can we capture the most timely user opinions. Finally, discussions among netizens on social media are completely spontaneous, more authentically reflecting their thoughts and attitudes. Traditional public opinion surveys are affected by factors such as sample representativeness and questionnaire design, limiting their authenticity.

Research methods for analyzing social media text can be divided into two categories: pre-constructed dictionary-based methods and machine learning algorithm-based methods [11-14]. Among them, pre-constructed dictionary-based methods have advantages in three aspects: universality, convenience, and flexibility. First, universality refers to whether a method can be applied to different domains and scenarios, process data on different topics, and output stable results. In text analysis, words are the core and foundation of language, the most basic tool for expressing and transmitting information. Dictionaries are based on systematic and regular understanding of language, mining the views and attitudes expressed in texts from words, and are therefore less restricted by topic [15]. Machine learning methods, however, rely on pre-trained datasets and require collecting and annotating large amounts of text data according to different domains and scenarios, using complex algorithms to train models for identifying text sentiment [16]. These models are often only applicable to specific domains, and if new problems arise, they may require re-collecting data and retraining models [17, 18]. Second, dictionaries offer greater convenience. After construction, sentiment dictionaries do not need adjustment for a period, have simple analysis steps, and can process large amounts of data in a short time. Dictionary identification results are also more intuitive, easier to analyze, and have higher interpretability. Machine learning-based sentiment identification can be divided into supervised and unsupervised learning. Supervised learning has high costs for manual annotation in the early stage, while unsupervised learning has limited interpretability of results, requiring researchers to make deductions based on theory, hindering its application and promotion in reality. Finally, dictionary analysis also has higher flexibility. Flexibility refers to researchers' need to adjust analysis methods and strategies according to research purposes during analysis to maximize text information mining effects, which pre-constructed dictionaries can satisfy. For example, when analyzing the relationship between moral outrage-related emotion intensity in Twitter and offline protest participation, researchers selected specific emotions, such as anger, from pre-constructed sentiment dictionaries to analyze subjects' tweets, thereby verifying hypotheses [19]. In summary, as a word-based method, dictionary analysis has advantages in universality, convenience, and flexibility. To meet practical analysis needs, we chose to construct a dictionary for sentiment analysis.

Currently, there are relatively mature sentiment dictionaries both domestically and internationally, such as SentiWordNet [20] and LIWC commonly used abroad, and HowNet [21] and Dalian University of Technology sentiment dictionary [22] domestically. However, these dictionaries face challenges in sentiment classification and vocabulary coverage, unable to meet the analytical needs of complex emotions in information incidents.

First, existing dictionaries' sentiment classification stops at polarity identification, including positive, negative, and neutral, unable to output more precise sentiment identification results, with corresponding refined research also lacking. The NTUSD Traditional Chinese Sentiment Dictionary from Taiwan University consists of 2,810 positive words and 8,276 negative words; the HowNet sentiment dictionary contains 4,566 positive sentiment words and 4,370 negative sentiment words. From an application perspective, in event analysis, current dictionaries can only simply determine whether public sentiment is mainly positive or negative, unable to assist in comparing and selecting more complex response strategies [23]. From a theoretical perspective, fine-grained emotion types under the same valence differ not only in intensity and target direction but also in their impact on individual behavior. For example, compared to negative emotions such as anxiety and sadness, anger has a stronger driving effect on individual participation in collective action [24-26]. In information dissemination, compared to happiness, information expressing anger spreads faster, and users whose anger is aroused are more active, enabling information to spread widely even in weak relationships [27]. The positive emotion "hope" can increase public support and recognition for policies [28]. Some existing dictionaries have attempted to refine identified emotions; for example, the Chinese sentiment dictionary developed by Dalian University of Technology provides a division of 7 major categories and 21 subcategories. However, this division is more semantically based, categorized according to dictionary categories, not based on emotion theory [22, 29]. Considering that the dictionary developed in this study serves public opinion monitoring, hoping to predict future behavior based on clarifying individual attitudes and emotions, a better choice is to construct fine-grained classification from emotion theory [30].

Second, existing dictionaries have low coverage of social media text, making comprehensive identification difficult. Currently, commonly used Chinese dictionaries are based on formal text content, such as modern Chinese adjective databases [29]. Formal text typically uses standardized language, follows certain grammar and format, and is suitable for formal occasions such as academic and legal contexts. Social media text, however, is short, informal, contains multiple modalities such as emojis [31], and is not constrained by grammar and format, being casual, flexible, and subjective, suitable for informal occasions such as entertainment and commentary. Furthermore, formal text usually uses traditional language, maintaining certain stability and consistency, while internet text has strong variability and diversity, with new vocabulary and usage constantly emerging. To achieve accurate identification of public emotions in social media, it is necessary to construct a corpus based on social media text and screen and expand keywords from existing dictionaries.

In summary, to address the above two problems, this study combines basic emotion theory and cognitive-appraisal theory to construct fine-grained sentiment classification, including 6 mood emotions, 11 stress emotions, and 33 evaluative emotions. Based on existing dictionaries, experts screened, categorized, and expanded keywords using a corpus of hot events from social media, ultimately forming the AnSi Chinese Emotional Attitude Lexicon (hereinafter referred to as the "AnSi Sentiment Lexicon"). We verified the lexicon's good performance in identifying fine-grained emotions through manual evaluation and event analysis. The dictionary construction method and the text data analysis method using this dictionary have been patented. Next, we will first introduce the dictionary construction process, divided into two parts: determination of fine-grained emotion categories and lexicon expansion. Then, we present the manual evaluation process and evaluation metrics, reporting the lexicon's identification results. To further verify the lexicon's validity in application, we analyzed two hot information incidents, the "Haitian Soy Sauce Double-Standard Incident" and the "Chengdu Girl Bitten by Dog Incident," reporting the results. Finally, we discuss the lexicon's contributions, limitations, and possible improvement methods.

2.1 Definition of Fine-Grained Emotion Categories

The Chinese sentiment dictionary most commonly used that provides fine categories beyond polarity classification is the Dalian University of Technology Sentiment Dictionary. During its development, researchers first based it on Ekman' s 6 major basic emotion categories and added one category "good" to more comprehensively depict positive emotions, ultimately obtaining 7 major emotion categories including "joy," "good," "anger," "sadness," "fear," "disgust," and "surprise" [32, 33]. They then referred to emotion categories obtained by Lin Chuanding and Xu Xiaoying et al. from word definitions, resulting in 20 emotion subcategories [29, 34].

This classification has two problems. First, the subdivision of 20 categories is based on dictionary definitions, obtained by scholars categorizing words in the Chinese word bank, but emotions existed before humans used language symbols, and the word categories in dictionaries also differ from those in social media. Therefore, subdividing emotions from emotion theory is a more ideal approach [35]. Furthermore, relying solely on basic emotion classification cannot cover netizens' emotional expressions. One core principle Ekman used when summarizing basic emotions was clear physiological arousal or response. However, in online environments, many netizens have not personally experienced events, their physiological arousal levels are correspondingly lower, and they mostly generate corresponding emotions based on evaluation and cognitive processes of information. For example, some researchers divided public negative crisis emotions in social media environments into three categories based on the "Integrated Crisis Mapping" (ICM) theory: attribution-unrelated emotions (such as anxiety, sadness, apprehension), attribution-related emotions (such as disgust, contempt), and self-examination emotions (such as embarrassment), with individual cognitive appraisal playing an important role [3, 36]. Therefore, we expanded emotion categories generated after individuals' cognitive evaluation of external stimuli based on cognitive-appraisal theory.

The proposal and development of emotion's cognitive-appraisal theory are based on two important observations. First, different individuals often have different emotional reactions to the same event. Second, the same individual may also have different emotions when facing the same event at different times. Arnold and Lazarus et al. believed this is because individuals' emotions arise from evaluation of external stimuli. Due to different evaluations, individuals produce different emotions when facing the same stimulus, thus introducing the cognitive process into the emotion process and constructing appraisal theory [37, 38]. Unlike most emotion theories, appraisal theory regards cognitive appraisal as the core of the emotion process, not just a part of it. Appraisal determines the intensity and type of behavioral tendencies, physiological responses, and ultimately induces behavior and emotion. Roseman proposed 5 dimensions that individuals use to evaluate situations based on appraisal theory [39], which was later expanded to 7 dimensions in 1996 by collecting individuals' ratings of appraisal factors in emotional experiences [40]. The specific dimensions are as follows:

(1) **Stimulus-Motivational Consistency.** Based on motivational consistency, people classify stimuli as motivated-consistent or motivated-inconsistent with individual motives. When external stimuli are consistent with individual motives, positive emotions are induced; when inconsistent, negative emotions are induced.

(2) **Motivational Appetitive/Aversive Nature.** Motives themselves can be divided into approach and avoidance categories. Appetitive motives represent individuals' tendency to maximize rewards, while aversive motives represent the tendency to minimize punishments. For example, when an individual believes an external stimulus can maximize rewards, an evaluation consistent with motives induces "joy," while inconsistency induces "sadness." Similarly, when an external stimulus can minimize punishments, consistency induces "relief," while inconsistency induces "distress."

(3) **Stimulus Unexpectedness.** Unexpected stimuli induce "surprise." This is only affected by whether the event is unexpected to the individual, regardless of its valence, so "surprise" is also classified as a neutral emotion.

(4) **Stimulus Certainty.** When individuals are aware of stimuli, they can be divided into certain and uncertain categories based on predictability. For example, when a stimulus is consistent with individual motives, if the individual can foresee the stimulus occurrence, they will feel "joy" or "relief" ; if unforeseeable, they will feel "hope."

(5) **Stimulus Attribution Target.** Based on individuals' attribution of event stimuli, they can be classified as self-caused, others-caused, or circumstance-caused. For example, when an individual believes others have triggered rewards or prevented punishments, they will generate "affection" ; conversely, they will generate "dislike."

(6) **Stimulus Controllability.** Based on controllability, stimuli can be divided into high and low controllability categories. High controllability means the individual believes the event stimulus is controllable and can be coped with. For example, when an event stimulus is inconsistent with motives, if the individual attributes this stimulus to external environmental categories, high controllability evaluation induces "frustration" and "disgust," while low controllability evaluation induces "fear," "sadness," and "distress."

(7) **Stimulus Characterological Nature.** After attributing events to others or self, they can be further divided into behavioral and characterological factors based on characterological nature. For example, when an individual believes others' behavior caused a negative event, they will feel "anger" ; when they believe others' character caused it, they will feel "contempt."

Based on the above 7 dimensions, Roseman summarized 17 emotions and verified the distinguishing dimensions through experiments, see Figure 1 [Figure 1: see original paper].

The above emotions can be further subdivided, especially "affection" and "dislike." First, when an individual attributes motivation-consistent stimuli to the environment and they are unforeseeable, the "hope" emotion can be further divided into "wish" (approach) and "optimism" (avoidance) based on appetitive/aversive nature. The "fear" emotion induced by motivation-inconsistent stimuli can also be divided into "anxiety" (approach) and "fear" (avoidance) based on appetitive/aversive nature. The "frustration" emotion can be divided into "setback" (unforeseeable) and "disappointment" (foreseeable) based on certainty. Among emotions induced by others-attributed stimuli, "affection" can be further divided into "affection," "praise," "satisfaction," and "trust" based on stimulus controllability and characterological nature. The "dislike" emotion can be divided into "question," "doubt," "blame," and "resentment" based on appetitive/aversive nature and certainty. Finally, the "regret" emotion induced by self-attributed negative stimuli can be divided into "regret" and "helplessness" based on appetitive/aversive nature. Ultimately, we determined 28 evaluative emotions, see Figure 2 [Figure 2: see original paper].

The above 28 fine-grained emotions provide relatively comprehensive coverage of emotions induced after individuals' cognitive evaluation of external information stimuli. Considering that the above classification lacks classification of individuals' physiological states and corresponding basic emotions, we incorporated basic emotions summarized by Ekman and Cordaro as supplements [33]. Ekman et al. believed basic emotions have the following characteristics: corresponding to unique physiological features, spontaneously generated, fast arousal, and short duration, based on this they proposed 7 basic emotions: anger, fear, surprise, sadness, disgust, contempt, and happiness. However, Ekman' s definition of basic emotions emphasizes that such emotions have fast arousal, high intensity, and short duration, but Russell pointed out that there is another category of emotions with lower intensity, longer duration, and lacking specific triggering events, which are often related to mood disorders, such as "depression" and "anxiety" [41, 42]. Based on the differences between these two types of emotions in physiological arousal intensity and duration, we define the former as stress emotions and the latter as mood emotions. Thus, we divided emotion categories into 3 major categories: mood emotions, stress emotions, and evaluative emotions, establishing a preliminary framework for fine-grained emotion categories. Considering the application needs of social media text sentiment analysis, we gradually added more advanced and complex emotion categories in subsequent information event processing, such as loneliness and compassion, and merged emotions with low discriminability, such as regret and guilt, ultimately obtaining 50 fine-grained emotions. The specific classification is as follows:

(1) **Mood Emotions:** Low arousal, long-duration emotional experiences, including loneliness, numbness, calmness, depression, anxiety, decadence.

(2) **Stress Emotions:** High arousal, limited-duration emotional experiences,

including happiness, fear, surprise, anger, sadness, excitement, relief, anxiety, tension, being moved, alertness.

(3) **Evaluative Emotions:** Emotional experiences generated after individuals evaluate information events, which can be further divided into two categories based on whether they point to netizens themselves or the external world. External-directed emotions include compassion, indifference, sarcasm, disgust, blame, resentment, questioning, affection, satisfaction, praise, trust, contempt, gratitude, admiration, longing, jealousy, helplessness, hope, optimism, wish, disappointment. Internal-directed emotions include dejection, embarrassment, inferiority, shyness, guilt, pride, setback, distress, anxiety, grievance, doubt, boredom.

2.1.1 Integration and Streamlining Based on General Dictionaries

We merged existing commonly used sentiment dictionaries, including the Dalian University of Technology Sentiment Dictionary, HowNet Sentiment Dictionary, Harbin Institute of Technology Sentiment Dictionary, and input method dictionaries to form an initial word bank, which was then screened and categorized by experts. First, we removed extremely low-frequency and obscure words, such as idioms like "佐饔得尝" (helping to prepare food and getting a taste) and "俎樽折冲" (diplomatic negotiations) that are almost never used in daily life. Then, we categorized words according to the definitions of the 50 emotion categories, retaining words with classification consistency above 75% to enter the dictionary, forming a seed word bank.

2.1.2 Expansion Based on Social Media Corpus

On the basis of the seed word bank, to achieve accurate identification of social media text, we crawled text from social media platforms including Weibo, Toutiao, Douyin, Kuaishou, and Xiaohongshu, using information events as units to form an expansion corpus. This mainly included food safety-related events, such as the "2017 European Toxic Egg Incident" (48,195 text messages) and the "2017 Nanchang Kindergarten Collective Poisoning Incident" (2,538 text messages), and tourism-related events, such as the 2018 Heilongjiang "Snow Town Tour" negative public opinion incident (419,154 text messages). We segmented the text, sorted it by word frequency, and analyzed the top 100 words. After excluding sentiment words already existing in the seed word bank, experts categorized them, supplemented by word frequency as a classification indicator. Overall, during the expansion process, experts added new words from the social media corpus to the dictionary. For phrases and emojis that might cause segmentation disagreements, we added regular expressions, phrases, and emojis directly into the dictionary without segmentation for direct identification. The final dictionary was formed, with the overall process shown in Figure 3 [Figure 3: see original paper].

3 Dictionary Validity Verification

After establishing the Chinese sentiment dictionary, we adopted two methods to test its validity: manual evaluation and event analysis. First, using manual classification results as the standard, we compared the lexicon' s effectiveness and accuracy in sentiment classification. Then, we used the lexicon to analyze two information incidents to verify the advantages of fine-grained sentiment classification in sentiment identification and application.

3.1 Manual Evaluation

To assess the lexicon' s accuracy in fine-grained sentiment identification, we first adopted a manual evaluation method to compare the consistency between manual sentiment classification and lexicon identification results. The experiment was pre-registered.

(1) Experimental Materials: On the premise that each emotion category contained more than 10 comments, we conducted random sampling based on the proportion of each emotion' s hits in the event information corpus, extracting a total of 1,860 comments. Each comment hit a single keyword, with 1,576 comments hitting text-based keywords and the remaining 284 comments hitting emoji-based keywords.

(2) Experimental Procedure: To ensure experimental quality, we recruited current students to complete experimental tasks in a computer lab. After entering the lab, participants first read instructions understanding that their task was to determine the emotion category of keywords (including text keywords and emojis, with keywords highlighted) in presented comments. For each comment, participants were presented with 5 emotion categories. In addition to the target emotion (lexicon emotion category), 2 emotions with consistent valence and 2 with inconsistent valence were randomly selected as distractors. For example, when the target emotion was positive, 2 negative emotions and 2 positive emotions were simultaneously presented.

Each participant completed judgments of emotion categories for keywords in 300 comments. To reduce fatigue effects on response quality, the experiment was divided into five blocks of 60 comments each. Participants rested for 1 minute between the first three blocks before proceeding to the next block task, and the rest time was extended to 2 minutes between the last two blocks. Attention test questions were set in the questionnaire, and participants who failed attention test questions were excluded. During the experiment, participants were provided with definitions of the 50 emotion categories and text corresponding to emojis as references.

(3) Participants: A total of 229 current students were recruited, 52% female, with an average age of 23. Educational distribution was 72% undergraduate, 21% master' s, and 7% doctoral. 40% of participants frequently browsed Weibo, and 37% frequently browsed Weibo comments.

(4) Evaluation Metrics: Based on signal detection theory, we evaluated lexicon identification results using manual evaluation emotion categories as the benchmark. According to the combination of manual evaluation emotion categories and lexicon identification emotion categories, four situations were divided: true positive (TP), false positive (FP), true negative (TN), and false negative (FN), obtaining a confusion matrix, see Table 2 . Four metrics can be obtained based on the confusion matrix [43].

The main evaluation metrics for text classification are accuracy, precision, recall, and F1 score, with accuracy and F1 score being more commonly used. The formulas and definitions are as follows:

Accuracy $= \frac{TP+TN}{TP+FP+FN+TN}$, representing the proportion of cases where manual and lexicon judgments are consistent out of all cases.

Precision $= \frac{TP}{TP+FP}$, representing the proportion of correct predictions (i.e., consistent with manual) among lexicon hits on target emotions.

Recall $= \frac{TP}{TP+FN}$, representing the proportion of lexicon correctly identifying corresponding emotions among manual hits on target emotions.

F1 Score $= \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$, the harmonic mean of precision and recall.

(5) Experimental Results: The sentiment dictionary performed well in identification, with mean accuracy, precision, recall, and F1 score for 50 emotions being 88%, 72%, 71%, and 69% respectively, see Table 3 . Results for text keyword identification were 89%, 74%, 73%, and 71% respectively on each metric, while emoji keyword identification results were 86%, 65%, 69%, and 62% respectively.

(6) Discussion: Using manual evaluation as the standard, the lexicon performed well in fine-grained emotion identification. Since previous studies basically divided classification into positive, negative, and neutral emotions without fine-grained emotion category test results, we used their ranges as references, see Table 4 . The accuracy range for sentiment dictionary construction is 0.56~0.90, recall range is 0.49~0.98, precision range is 0.49~0.61, and F1 score range is 0.49~0.89; the accuracy range for machine learning construction is 0.68~0.92, and F1 score range is 0.69~0.84. Our lexicon achieved above-average performance on all four metrics.

3.2 Event Analysis

To further verify the lexicon' s effectiveness, we used it to analyze netizens' emotions in information incidents, providing references for event analysis based on fine-grained emotion identification. Considering that this lexicon was constructed to analyze information incidents in social media, we selected the "Haitian Soy Sauce Double-Standard Incident" and the "Chengdu Girl Bitten by Dog Incident" as analysis objects, corresponding to corporate public opinion and social event public opinion respectively. Selection reasons include three points: First, both incidents had high popularity and discussion volume, with rich text content on social media for analysis; second, netizens expressed relatively complex emotions in both incidents, which could not be fully analyzed by categorizing them as positive or negative, requiring in-depth fine-grained analysis; third, the main discussion object in the Haitian Soy Sauce Double-Standard Incident was Haitian Enterprise, while the Chengdu Girl Bitten by Dog Incident included multiple parties such as the dog and its owner, the girl and her parents, and crowdfunding platforms like Qingsongchou. Analyzing these two incidents can provide evidence for the lexicon' s effectiveness in both corporate-related and social event-related public opinion analysis.

(1) "Haitian Soy Sauce Double-Standard" Incident

In mid-September 2022, internet celebrity blogger Xin Jifei released a video "How to Blend Soy Sauce with Water and Additives." Shortly after the video' s release, some netizens revealed that Haitian' s soy sauce ingredient list contained additives from the video, putting Haitian soy sauce in the spotlight. Subsequently, some overseas netizens claimed that Haitian soy sauce they purchased abroad contained no additives at all, accusing Haitian Group of double standards. This incident quickly triggered high levels of public attention, with popular topics and short videos forming on Weibo, Douyin, and other platforms.

A. Data Collection and Preprocessing: The questioning of Haitian soy sauce additives originated on short video platforms. To ensure data comprehensiveness, researchers crawled data from Kuaishou, Douyin, Toutiao, and Weibo platforms. Using "Haitian" + "soy sauce" as keywords, we crawled all hit texts from September 30, 2022, to October 9, 2022, performed deduplication, and cleaned irrelevant texts such as entertainment news and stock trading, obtaining 139,901 data entries.

B. Event Process: Changes in social media discussion volume during the Haitian soy sauce incident are shown in Figure 4 [Figure 4: see original paper]. Key turning points include Haitian' s two responses and the Food Industry Association' s clarification. On the evening of September 30, 2022, Haitian Flavoring Industry first responded that additive usage in all products complied with relevant standards and would take legal action against rumor-mongering. On the evening of October 4, facing escalating public opinion, Haitian Flavoring Industry issued another statement denying double standards. The China Condiment Industry Association subsequently issued a statement backing the enterprise. On October 5, Red Star News reported that Haitian Flavoring Industry was included among the drafting standard units for the soy sauce industry, triggering a new wave of public opinion. On October 6, the China Food Industry Association released "Several Issues Needing Clarification Regarding the 'Soy Sauce Storm,' " explicitly responding to a series of questions and clarifying that Japanese soy sauce standards are not higher than China' s standards, after which discussion popularity gradually decreased to zero.

C. Sentiment Analysis Results: Overall netizen sentiment was predominantly negative, reaching 69% in our lexicon' s identification results, with positive and neutral sentiments accounting for 25% and 6% respectively, changing over time as shown in Figure 5 [Figure 5: see original paper]. Considering that likes can reflect netizens' support for a certain viewpoint, we weighted sentiment word frequency using logarithmized like counts [49].

Further analysis of negative sentiment internals revealed that "blame" and "doubt" emotions dominated and showed basically consistent trends, see Figure 6 [Figure 6: see original paper]. First, as a domestic brand, netizens believed that Haitian' s exported and domestically sold products differed in quality, which was "double-standard" behavior, causing dissatisfaction and generating "blame" emotion. Haitian Flavoring Industry' s two responses on September 30 and October 5 actually failed to meet netizens' expectations, only responding to compliance with standards without answering why domestic and foreign standards were inconsistent, triggering "doubt" emotion. For example, "What people question is why your products exported abroad have no additives, while those sold domestically have so many types? You respond with 'complying with national standards' and even threaten to hold rumor-mongers legally responsible. It' s really 'talking at cross purposes,' evasively talking nonsense. People are questioning the facts, why can' t you just respond directly?"

The concentrated expression of "doubt" emotion corresponds to the expectation gap between enterprises and the public, where enterprises believe they have met public expectations but actually cannot satisfy them [52, 53]. Haitian Flavoring Industry believed that production meeting national standards was product quality assurance, but the public believed this standard should be a minimum rather than maximum. The "blame" emotion reflects that the public tends to form evaluations based on "care-based trust" rather than "competence-based trust" [54]. Earle proposed that the goal of care-based trust is solidarity, while the goal of competence-based trust is accuracy [55]. Haitian only expressed that additive usage complied with regulations in its response, attempting to reconstruct "competence-based trust," but ignored "care-based trust," failing to explain why products sold domestically and abroad had different standards, which not only failed to quell public opinion but instead triggered public blame emotions. Combined with sentiment analysis results, in this incident, enterprises should prioritize reconstructing care-based trust, standing from the public' s position, conveying the importance attached to domestic consumers as a Chinese brand, responding to whether there is double standards; further, answering questions existing in the public' s mind about additive usage, helping the public scientifically understand additives, thereby changing their attitudes toward additive usage [56].

(2) Chengdu Girl Bitten by Vicious Dog Incident

On October 16, 2023, a two-and-a-half-year-old girl was severely injured by an unleashed Rottweiler while walking, triggering public concern. On October 18, fearing surgical expenses, the girl' s family initiated a 2 million RMB fundraising campaign on the Qingsongchou platform and raised the full amount within 3 hours. Many netizens raised questions, pointing out that the 2 million fundraising amount was excessive given that the property management and dog owner had already advanced surgical fees and the hospital had opened a green channel. On October 23, after the girl was transferred to a general ward, Qingsongchou platform discussed with the girl' s family and refunded all unused donations. The girl was finally discharged on November 14, with total surgical expenses amounting to over 80,000 RMB.

A. Data Collection and Preprocessing: In the Chengdu girl bitten incident, netizen discussions concentrated on the Weibo platform. Therefore, we used "bitten girl" as the keyword to collect all hit blog posts and comment content from October 16, 2023, to November 17, obtaining 128,554 data entries, which after deduplication and cleaning yielded 122,654 data entries for analysis.

B. Event Process: Changes in Weibo platform discussion volume during the Chengdu girl bitten incident are shown in Figure 7 [Figure 7: see original paper]. Key nodes include: On the afternoon of October 16, 2023, police reported that a two-and-a-half-year-old girl was bitten by an unleashed black Rottweiler in Chengdu' s Chongzhou Hengda Xichen Oasis residential complex, causing over 20 bites and right kidney contusion and laceration, triggering public concern. On the afternoon of October 17, the dog owner, Tang, was taken into custody, and police took criminal coercive measures according to law. On October 18, fearing subsequent treatment costs, the girl' s family initiated a 2 million RMB fundraising campaign on Qingsongchou platform, raising the target amount within 3 hours. Since the girl' s family initiated fundraising, netizens' controversy over whether the fundraising amount was excessive gradually heated up. On October 22, Qingsongchou platform stipulated that "when a single fundraising amount exceeds 500,000 RMB, written proof from a medical institution must be submitted." Huaxi Hospital responded that "no relevant cost proof was issued," triggering public questioning again. Around 9 PM on October 23, Huaxi Hospital released treatment progress, stating the girl had been transferred to a general ward with nearly 60,000 RMB in medical expenses. Around 10 PM, the topic of over a thousand netizens applying for refunds topped Weibo' s hot search. On October 25, Qingsongchou announced it would refund all donations. Around 10 AM on October 27, the Qingsongchou platform showed that the girl' s 2 million RMB donations had been fully refunded. On November 1, according to information provided by doctors participating in the girl' s treatment consultation at Huaxi Hospital, the girl' s right kidney had been saved, her condition was stable, and recovery was good. On November 8, a man from Anhui reported that his daughter was bitten by a dog causing disfigurement, triggering netizens' heated discussion of this incident again. On November 14, after active treatment at the hospital, the bitten girl had normal liver and kidney function, smooth recovery of all body systems, good wound healing, and was discharged. During hospitalization, the hospital' s manual payment window received a total of 220,000 RMB in advance payments, with over 80,000 RMB used.

C. Sentiment Analysis Results: Overall sentiment was predominantly negative, reaching 61%, followed by positive and neutral sentiments accounting for 24% and 15% respectively, changing over time as shown in Figure 8 [Figure 8: see original paper].

This incident involved multiple parties: the dog and its owner, the girl and her family, relevant government departments, etc., among which netizens' attitudes toward the girl and her family changed multiple times. Next, we analyzed sentiments related to the girl's family. Using keywords such as "mother,""father," and "family" to filter text information related to the girl' s family, we obtained 6,848 blog posts and comments. Overall sentiment remained predominantly negative, accounting for 58%, with positive and neutral sentiments accounting for 24% and 18% respectively, changing over time as shown in Figure 9 [Figure 9: see original paper].

To further understand changes in netizens' emotions toward the parents during the event process, we analyzed the top 3 emotions in negative sentiment: blame (negative, 17%), doubt (negative, 12%), and sadness (negative, 6%), with their changes shown in Figure 10 [Figure 10: see original paper] between October 16 and October 30.

From Figure 10, we can see that the three negative emotions showed large differences in their changes over time. When police released the incident announcement on October 16, netizens on one hand felt "sadness" for the injured girl' s family, hoping the girl could receive timely assistance. For example, "The little girl who was bitten is not yet three years old, with over 20-30 wounds all over her body, her kidney is already ruptured, bringing a lifetime of shadow to the child. No amount of money can heal the child' s psychological harm and physical health. The dog owner must be held responsible and must pay a heavy price. Only 2 and a half years old, how grief-stricken her mother must be." At this time, as many incident details had not been disclosed and were in a highly uncertain state, the intensity of "blame"and "doubt"emotions was also high. For example, "Why did the dog suddenly go crazy? Why wasn' t the dog leashed? Why do similar incidents happen repeatedly? Whose responsibility is this?"

On October 17, after the dog owner was taken into custody, the situation gradually became clear, netizens' "doubt" emotion significantly decreased, and "blame" emotion reached its peak. However, after the girl' s family initiated fundraising on October 18, "doubt" emotion rose to its highest point, while "blame" and "sadness" emotions both decreased. This trend corresponded to netizens' questions about the reasonableness of the fundraising amount by the girl' s family, such as "Since the vicious dog owner is willing to compensate, why still seek social donations?" and "If the fundraising amount is too large, should regulatory authorities intervene? Will the girl' s parents disclose details later?"

In the subsequent period, netizens continuously posted information about the girl' s mother, including her search history and past usernames, containing much false information. Although the girl' s family and their lawyer responded to rumors and official institutions also refuted them, none dispelled netizens' negative emotions. In this stage, "blame" emotion intensity continuously rose, while "doubt" and "sadness" emotions remained low, indicating that netizens' discussions became increasingly irrational, evolving into emotional venting. After Huaxi Hospital responded on the 22nd that it had not provided medical proof, "blame" emotion reached its third peak, with netizen comments such as "Using the injured child to make money, greedy parents and the organization behind them have exhausted everyone' s only kindness. People who truly need money bear the consequences." It was not until Qingsongchou announced on October 25 that it would refund all unused donations that "blame" emotion fell back to a low point.

In the "Chengdu Girl Bitten by Vicious Dog" incident, netizens' emotions were predominantly negative, but inconsistent change trends emerged within negative emotions. From the incident occurrence to the dog owner being taken into custody, as the incident gradually became clear, "blame" and "sadness" emotions with clear targets showed obvious increases, while "doubt" emotion decreased. When the parties acted inconsistently with social expectations and triggered public discussion, "doubt" emotion became dominant, with netizens questioning whether help should be sought and the amount of help. In the later stage, they repeatedly questioned whether the Qingsongchou process was formal. However, although the girl' s family and Qingsongchou responded to some questions, they did not effectively alleviate the public' s negative emotions toward them, with "blame" emotion becoming dominant, finally erupting after the girl was transferred to a general ward and only falling back to a low point after Qingsongchou announced it would refund all unused donations.

The public' s emotional attitudes toward the bitten girl' s parents in this incident reflect that most people still believe individuals only have the right to seek external help when they are "desperate." However, with social development, people should recognize that recipients are not always on the edge of despair; they may be facing emergencies, major diseases, or other unforeseen difficulties. Society should provide more flexible and inclusive support mechanisms to help them solve problems. For crowdfunding platforms represented by Qingsongchou, their image was impacted in this incident, suggesting that platforms need to re-examine and adjust their fundraising strategies. Platforms must not only ensure the reasonableness of fundraising amounts but also strengthen the review of fundraising project authenticity, guarantee information transparency and truthfulness, to maintain public trust.

(3) Discussion

In this study, we used the fine-grained Chinese sentiment and attitude lexicon to analyze two hot incidents: the "Haitian Soy Sauce Double-Standard Incident" and the "Chengdu Girl Bitten by Dog Incident." We found that although netizens' emotions in both incidents tended to be negative overall, there were obvious differences within negative emotions. This difference was reflected not only in emotion types but also in emotion change patterns and trends. For example, in the "Haitian Soy Sauce Double-Standard Incident," the public' s "doubt" and "blame" emotions showed synchronous change characteristics, while in the "Chengdu Girl Bitten by Dog Incident," these two emotions showed opposite change trends.

Comparing the emotion change patterns in the two incidents, we found that in the "Haitian Soy Sauce Double-Standard Incident," effective corporate responses could alleviate the public' s "doubt," thereby reducing "blame" emotion. This indicates that in some cases, timely communication and response can effectively guide and improve public emotions. However, in the "Chengdu Girl Bitten by Dog Incident," despite multiple responses from the family and lawyers, the public's "doubt" was not effectively alleviated and might transform into stronger "blame" emotion. This phenomenon suggests that emotion transformation is not a simple linear process but is influenced by multiple complex factors.

This comparative analysis result not only reveals the complexity within negative emotions but also highlights the importance of fine-grained sentiment analysis in event analysis. Fine-grained analysis can provide more precise emotion identification and trend prediction, helping us deeply understand the subtle changes and internal logic of public emotions. This in-depth analysis can not only improve the accuracy of emotion identification but also provide richer and more targeted information for enterprises and governments, supporting them in more effectively formulating and evaluating response strategies. For example, in the "Haitian Soy Sauce Double-Standard Incident," enterprises can reduce "blame" emotion by strengthening communication with the public and actively responding to public concerns. In the "Chengdu Girl Bitten by Dog Incident," the family and lawyers may need to adopt more in-depth and comprehensive measures to truly resolve the public' s "doubt" and alleviate "blame" emotion.

4.1 Research Summary

After entering the information age, the widespread coverage of mobile devices and social media has broken original communication barriers and weakened the central position of traditional media. Once network public opinion triggered by information incidents erupts, "fragmented" information can bring unpredictable consequences after online fermentation, catching governments and enterprises off guard. Therefore, establishing a public opinion early warning mechanism adapted to social media communication is very important. The text content left by netizens on social media is the key channel for obtaining information. Among them, netizens' emotions not only represent their attitudes and cognitive evaluations but further influence information dissemination and subsequent behaviors, requiring the development of reliable tools to accurately identify emotions in massive data.

Compared with algorithmic classification, sentiment dictionaries, starting from words, have higher universality, convenience, and flexibility. However, current commonly used dictionaries such as NTUSD and HowNet only provide positive-negative classification, requiring more fine-grained sentiment identification in practical analysis to provide feasible suggestions, especially since fine-grained emotions within positive and negative emotions differ in direction and intensity. Furthermore, these dictionaries are all based on relatively formal long articles and Chinese dictionaries, while social media text is short, mostly informal, and more diverse in format, with low coverage by existing dictionaries. To address these two problems, this study, based on emotion cognitive-appraisal theory, further subdivided 28 evaluative emotions on the basis of the 7 evaluation dimensions proposed and verified by Roseman, fused basic emotions and mood emotions to obtain 50 fine-grained emotions, and then had experts first screen and categorize existing dictionaries, then expand the dictionary based on a corpus of multiple hot events, ultimately obtaining the fine-grained Chinese sentiment and attitude lexicon.

To test the lexicon' s validity, researchers used two methods: manual evaluation and event analysis. In the manual evaluation experiment, the lexicon' s identification accuracy reached 88%, and F1 score reached 66%, with each emotion category performing well on accuracy, precision, hit rate, and F1 score, showing high consistency with manual classification results. In event analysis, based on discussion popularity and event type, we selected the "Haitian Soy Sauce Double-Standard Incident" and the "Chengdu Girl Bitten by Vicious Dog Incident." By comparing event processes and information disclosure nodes, we found that netizens' emotion changes obtained through lexicon analysis corresponded to key events and conformed to theoretical expectations. More importantly, we observed different changes in fine-grained emotions within the same valence, which not only verified the advantages of fine-grained analysis in public opinion monitoring but also provided new possibilities for selecting appropriate response strategies based on analysis results.

4.2 Lexicon Advantages

Compared with previous dictionaries, this lexicon has two advantages: First, we added evaluative emotions based on cognitive-appraisal theory on the basis of original dictionaries, expanding original positive-negative polarity to mood, stress, and evaluative emotions. This lexicon is based on classification derived from classic emotion theory, overcoming the limitations of previous studies that could only provide positive-negative classification or classification based on word meaning. In current discussions of public opinion dissemination, researchers no longer stop at positive-negative emotion classification but discuss the impact of fine-grained emotion changes on individual attitudes and behaviors based on theory. For example, when analyzing whether the government' s crisis response strategy was effective in the "12.20 Shenzhen Landslide Accident," researchers focused on emotions such as "sadness," "support," "anger," "fear," and "anxiety." Among them, "sadness" emotion unrelated to attribution does not directly affect the public' s evaluation of the government, while "anger" emotion with clear directionality damages the government' s image. After analyzing a series of government Weibo posts and their comment sentiments, they found that timely updates on rescue situations and visits to families of missing persons received relatively positive evaluations, which not only comforted the emotions of those directly involved but also satisfied the information needs of most non-involved public. However, limited by the lack of analysis tools, researchers included less text in their analysis. The lexicon provided in this study can meet this analysis need. Similarly, for studies currently limited by processing costs and speed and using experiments or questionnaires for verification, this lexicon can also be used to verify the applicability of theory in real-world contexts.

Second, this lexicon expanded keywords based on a social media corpus, significantly improving the lexicon' s identification rate for social media text. With the continuous development of the internet, the time people spend on social media daily also continuously increases. Correspondingly, information flowing in social media also shapes the public' s attitudes toward specific events and influences their subsequent behaviors. For example, studies continuously find that social media use affects individuals' trust in government and other official institutions. Publishing content on social media that receives recognition from others increases the likelihood of participating in offline activities [19]. This lexicon improves identification rates for social media text by crawling multiple hot information events to form a corpus for dictionary expansion. Considering the fast update speed of social media text, this lexicon also introduces machine learning algorithms for continuous expansion and updating.

4.3 Application Contributions

The fine-grained sentiment lexicon constructed in this study has applications in public opinion monitoring, corporate consulting, and commodity consumption.

First, fine-grained sentiment identification technology provides governments with new tools for real-time monitoring and feedback of public emotions. Through this technology, governments can timely capture and analyze emotion trends, providing data support for rapid response to public opinion incidents. This real-time monitoring not only helps governments understand current emotional states but also predicts possible emotional changes, enabling more effective response measures in public opinion crisis management [57]. In policy formulation and adjustment, fine-grained sentiment lexicons enable governments to deeply analyze the impact of different policies or events on public emotions, thereby adjusting or formulating policies that better meet public emotional needs. This emotion-oriented policy formulation helps improve public acceptance and effectiveness of policies. Lexicon application can also help governments balance the views and emotions of different social groups, promoting social fairness and harmony. By identifying and understanding the emotional needs and expectations of different groups, governments can better balance the interests of all parties in policy formulation and implementation.

Second, fine-grained sentiment identification technology provides enterprises with the ability to deeply understand consumer emotions. Enterprises can more accurately understand consumer needs and preferences by analyzing consumer expressions on social media, customer feedback, and market research. This insight helps enterprises make product development and market positioning decisions that better meet market demands. In brand management and reputation maintenance, fine-grained sentiment lexicons can help enterprises monitor consumers' emotional attitudes toward brands, timely discover and respond to negative emotions that may damage brand image. By tracking emotional changes in real time, enterprises can quickly respond and take effective measures to maintain brand reputation. Lexicons can also serve customer service optimization by analyzing emotional exchanges between customers and enterprises during interaction processes to identify service process deficiencies. Enterprises can optimize customer service processes and improve customer experience and satisfaction based on this information.

4.4 Lexicon Limitations and Optimization

(1) Identification of Irony and Other Statements. In social media, irony is a common rhetorical device that conveys specific emotions or attitudes by expressing meanings opposite to actual intentions. Currently, natural language processing technology faces challenges in identifying ironic statements because irony often relies on complex interactions of context, tone, and speaker intent. The choice of training sets has a direct impact on model identification ability, and the generalization ability of existing models still needs improvement. In the future, researchers can explore introducing large language models, utilizing their deep semantic understanding and rich contextual information processing capabilities to optimize irony statement identification. Additionally, combining knowledge from fields such as affective computing, pragmatics, and psychology can be considered to improve models' understanding and identification of irony.

(2) Processing of Negative Expressions. Negative expressions are a complex issue in sentiment analysis because they can change the sentiment polarity of sentences. The current identification rule adopted in the lexicon is to merge negative words with following words, not identifying the following words as matching emotions. This processing method can significantly improve identification accuracy but also ignores some pseudo-negative combinations containing negative words and other negative combinations not containing negative words. To solve this problem, researchers are trying to improve word segmentation technology to more finely distinguish the combination methods of negative and non-negative words, and explore adding specific negative expressions to the lexicon. Simultaneously, machine learning algorithms can be utilized to more finely classify the sentiment valence of negative expressions, rather than simply classifying them as neutral or opposite valence.

(3) Optimization of Word Sense Domain Characteristics. Word sense domain characteristics refer to words that may have different meanings and emotional colors in different domains or contexts. For example, some words may have positive meanings in the medical field but negative meanings in the legal field. To optimize the lexicon, researchers are trying to accumulate and summarize analysis rules through domain-specific corpora to more accurately capture words' emotional tendencies within specific domains. Additionally, domain adaptation technology can be utilized to enable the lexicon to dynamically adjust word meanings and sentiment classifications according to different domain contexts, improving the accuracy and adaptability of sentiment analysis.

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Note: Figure translations are in progress. See original paper for figures.