Information Processing and Management 61 (2024) 103609

Contents lists available at ScienceDirect

Information Processing and Management

journal homepage: www.elsevier.com/locate/infoproman

Emotion-cognitive reasoning integrated BERT for sentiment analysis of online public opinions on emergencies

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ARTICLE INFO

Keywords:
Emergency
Sentiment analysis
OCC model
BERT
Hybrid approach

ABSTRACT

Sentiment analysis of online public opinions on emergencies (OPOEs) requires accurate and explainable results to facilitate a better understanding of public sentiment and effective crisis management, but it is challenging due to the complexity and diversity of emotions contained in OPOEs. In this paper, we propose an Emotion-Cognitive Reasoning integrated BERT (ECR-BERT) for sentiment analysis of OPOEs. ECR-BERT combines an emotion model and deep learning to provide reliable auxiliary knowledge to improve BERT. Specifically, we use the emotion model proposed by Ortony, Clore, and Collins (OCC) to build emotion-cognitive rules and perform emotion-cognitive reasoning to discover emotion-cognitive knowledge. To mitigate the impact of knowledge noise, we propose a novel self-adaptive fusion algorithm that provides a selection mechanism for the incorporation of knowledge. In addition, we utilize knowledge-enabled feature representation to efficiently exploit inferred knowledge. Our evaluation on four real-world OPOE datasets shows that ECR-BERT significantly outperforms other BERT-based models, achieving state-of-the-art results with an absolute average accuracy improvement of 0.82%, 1.74%, 0.98%, and 1.37% over BERT, respectively. In addition, ECR-BERT provides a detailed explanation of how sentiment polarity is derived from fine-grained emotion categories. The ablation study demonstrates the effectiveness of each technique. In conclusion, ECR-BERT is an excellent choice for sentiment analysis of OPOEs, providing accurate and explainable results for crisis management.

1. Introduction

Emergencies, such as the Tianjin port explosion (Wikipedia, 2015) or the COVID-19 global pandemic (WHO, 2019), often lead to a surge of online public opinions, causing negative sentiment and posing a threat to social stability. To address this issue, researchers have applied sentiment analysis, a field that focuses on automatically extracting sentiment polarity (e.g., positive, negative, or neutral) from text, to analyze public sentiment during emergencies (Beigi et al., 2015). Sentiment analysis of Online Public Opinions on Emergencies (OPOEs) can help emergency management organizations and personnel understand the evolution of public sentiment during emergencies, empowering them to enhance their crisis response and management (Buscaldi & Hernandez-Farias, 2015; Nagy &

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https://doi.org/10.1016/j.ipm.2023.103609
Received 9 May 2023; Received in revised form 4 December 2023; Accepted 7 December 2023
Available online 19 December 2023
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Stamberger, 2012; Neppalli et al., 2017).

It is important to note that sentiment analysis of OPOEs differs from sentiment analysis in domains such as restaurants or e-commerce. In these latter contexts, individuals typically express their sentiments about specific entities in a straightforward manner. For example, opinions may state that a restaurant's service is excellent or that an online product is visually appealing. In contrast, during emergencies, the public tends to express sentiments about the event itself, and the expressions often contain complex emotions, making the sentiment analysis of OPOEs a challenging endeavor. In particular, sentiment analysis of OPOEs faces two main challenges compared to sentiment analysis in other domains:

- Sentiments reflect the overall polarity of OPOEs, which requires finer emotion characterizations (Wang et al., 2020). In some cases, OPOEs may contain emotions of conflicting polarity within a singular expression (Zhang & Ma, 2023), making the prediction of general polarity challenging. As illustrated in Fig. 1(a), a Weibo user's opinion during the COVID-19 is labeled as "negative" despite encompassing two emotions of opposite polarity: joy (positive) for good health and anger (negative) toward those causing disasters.
- The critical emotional details toward emergencies are crucial for the emergency responders, which helps them to think and reflect better for more effective crisis management during or after emergency events (Schulz et al., 2013; Singh et al., 2018). Although deep learning models perform well in sentiment analysis, they often fail to explain how the sentiment polarity is derived from the fine-grained emotion categories contained in the OPOEs. For example, in the aforementioned example in Fig. 1(a), deep learning models can predict its polarity as "negative", but lack the ability to provide detailed emotion categories (cf., Fig. 1(g)) as explanations, hindering a comprehensive understanding of the emergency.

To address these challenges, emotion models have been developed over decades that are able to recognize human emotion categories through easily understandable emotion labels or a common set of dimensions (PS & Mahalakshmi, 2017). These models offer a potential solution by facilitating reasoning computations. Moreover, the results of such reasoning not only serve as auxiliary knowledge to improve the performance of deep learning models, but also provide detailed emotion insights to explain the sentiment analysis results. Therefore, there is an urgent need for a hybrid approach to sentiment analysis that integrates an emotion model with deep learning to effectively address the aforementioned challenges. Fig. 1 provides a concrete example to illustrate the proposed research process. The numerical labels (1–5) embedded in the lines correspond to the order of the research process.

The emotion model proposed by Ortony, Clore, and Collins, known as the OCC model, is a classic emotion-cognitive appraisal model that provides a rule-based reasoning mechanism for sentiment analysis (Ortony et al., 1988). The cognitive-induced conditions of the OCC model can infer the different emotion categories contained in the OPOEs (Huangfu et al., 2013). We refer to this reasoning process as Emotion-Cognitive Reasoning (ECR), and the reasoning results as emotion-cognitive knowledge (cf., Fig. 1(b), (c)). Bidirectional Encoder Representations from Transformers (BERT), as an advanced pre-trained language representation model, has recently shown excellent performance in sentiment analysis due to its powerful semantic feature extraction capabilities (Devlin et al., 2019; Pota et al., 2021). Therefore, we combine ECR and BERT to construct a hybrid model, ECR-BERT, for sentiment analysis of OPOEs. Specifically, we perform ECR on OPOEs to infer emotion-cognitive knowledge and incorporate it into OPOEs to generate sentence-emotion trees, which serve as the input to BERT for sentiment polarity prediction (cf., Fig. 1(e)).

When generating sentence-emotion trees, too much incorporation of emotion-cognitive knowledge can distract OPOEs from their correct meaning, this is the so-called knowledge noise problem (W. Liu et al., 2020). Especially for OPOEs that contain complex and diverse emotions, incorporating emotion-cognitive knowledge into OPOEs without selection will exacerbate the knowledge noise. For

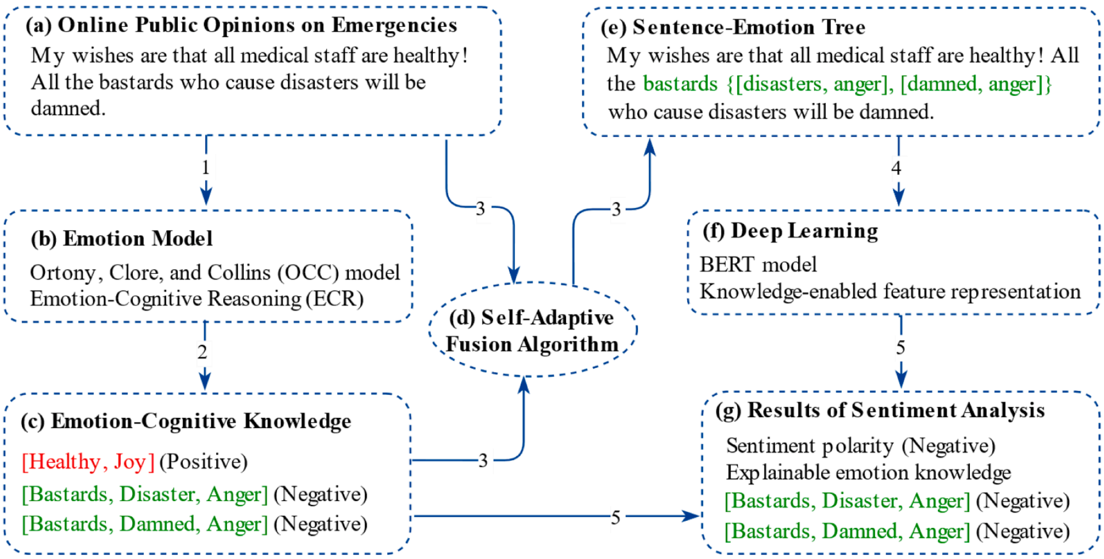

Fig. 1. A concrete example to illustrate our research concept.

example, we incorporate too much emotion-cognitive knowledge with positive polarity when the general sentiment tendency of the OPOE is negative. Therefore, we propose a self-adaptive fusion algorithm that provides a selection mechanism for knowledge incorporation to alleviate the knowledge noise problem (cf., Fig. 1(d)). For feature representation, the sentence-emotion tree is a tree structure that incorporates emotion-cognitive knowledge as branches in OPOE, traditional position embedding (Devlin et al., 2019) makes the sentence-emotion tree unreadable and loses its structural information. Inspired by (W. Liu et al., 2020), we adopt knowledge-enabled feature representation to make the use of inferred emotion-cognitive knowledge more efficient (cf., Fig. 1(f)).

The main contributions of our research are as follows:

- We study the explainable sentiment analysis of OPOEs using the OCC model to automatically infer the complex and diverse emotions contained in these public opinions.
- We propose a self-adaptive fusion algorithm that provides a selection mechanism for knowledge incorporation to effectively mitigate the knowledge noise problem.
- We propose a hybrid model, ECR-BERT, which uses the OCC model to perform reasoning and adopts knowledge-enabled feature representation to make the use of inferred knowledge more efficient.

The rest of this paper is organized as follows. In Section 2, we introduce and detail the work done on sentiment analysis of OPOEs. We describe the research objectives in Section 3, and Section 4 presents our method. A comprehensive evaluation is performed in Section 5. In Section 6, we discuss the main innovations and highlight their implications. Finally, Section 7 presents the conclusion and possible future directions.

2. Related work

2.1. Online public opinions on emergencies

During emergencies such as natural disasters, accidents, public health events, and social security incidents, people often use online platforms, particularly social media channels like Facebook, Twitter, and Weibo, to express their opinions, attitudes, and requests. This leads to the formation of online public opinions (Jin & Yang, 2018). The detection and analysis of sentiment in these online public opinions can provide useful insights for crisis management (Buscaldi & Hernandez-Farias, 2015; Nagy & Stamberger, 2012).

Several scholars have explored the utility of sentiment analysis in crisis management from various perspectives. Mandel et al. (2012) conducted an analysis of regional sentiment trends over time, while Neppalli et al. (2017) projected user sentiments onto a geographical map to examine spatial sentiment arrangements. Dong et al. (2013) and Kryvasheyeu et al. (2015) associated users' sentiments with disaster locations, which facilitates the resolution of aid problems (Varga et al., 2013). Jin and Yang (2018) suggested controlling strategies for the government by studying the evolution of public sentiment, while Yoo et al. (2018) provided users with an at-a-glance view of disaster events by predicting sentiment polarity contained in tweets related to natural disasters. Additionally, sentiment analysis of OPOEs has contributed to the identification of common sentiment patterns across different countries (Basiri et al., 2021). In contrast to these studies, which focus on two or three sentiment categories, some scholars study fine-grained emotional information in emergencies. Vo et al. (2013) classified tweets into five emotion categories and found that fear and anxiety were the two emotions expressed immediately after an event, while calmness and unpleasantness were not significantly expressed in small earthquakes but were exposed in large ones. Schulz et al. (2013) identified seven emotion categories from crisis-related micro-posts that provided highly crisis-relevant information. Torkildson et al. (2014) built a set of classifiers considering eight types of emotions and visualized them.

Previous literature has explored the significance of online public opinion sentiments or emotions in crisis management from different perspectives. However, these studies have not developed novel sentiment classification techniques that address the unique challenges of sentiment analysis of OPOEs. Instead, they have used well-known existing methods, such as Logistic Regression (Mandel et al., 2012), Naive Bayesian Networks (Mandel et al., 2012; Nagy & Stamberger, 2012; Schulz et al., 2013; Vo & Collier, 2013), Decision Trees (Mandel et al., 2012), Support Vector Machines (Jin & Yang, 2018; Schulz et al., 2013; Torkildson et al., 2014), Convolutional Neural Networks (Yoo et al., 2018), and a fusion-based model (Basiri et al., 2021). Zhang and Ma (2023) recently developed an ALBERT-based model enhanced with topic knowledge for sentiment analysis of OPOEs, which achieves high model accuracy and low memory consumption. However, the model that utilizes topic knowledge cannot provide explanations of emotion details. Therefore, it is challenging for these methods to achieve accurate and explainable sentiment analysis results of OPOEs.

2.2. OCC model for sentiment analysis

Emotion models are used by scholars to better understand and analyze complex human emotions. Existing emotion models, such as Plutchik's model (Plutchik, 1980) and Ekman's model (Ekman, 1992), have limitations in providing a rule-based mechanism for emotion export, making emotion reasoning difficult. The OCC model, a classic model of emotion appraisal in cognitive psychology, classifies emotions into 22 categories based on different cognitive-induced conditions (Ortony et al., 1988). The emotion-cognitive rules of the OCC model can be used to infer fine-grained emotion categories of OPOEs, with the inferential paths providing explanatory power for the results. However, the OCC model suffers from ambiguity and complexity, which limits its automatic reasoning feasibility. Steunebrink et al. (2009) identified ambiguities in the OCC model and proposed an inheritance-based emotional logic structure. In practice, researchers tend to simplify the emotion-cognitive rules of the OCC model.

Huangfu et al. (2013) utilized six emotion dimension values to represent the complex cognitive-induced conditions presented in the OCC models, achieving automatic emotion identification through an emotion dimension dictionary. Udochukwu and He (2015) used the OCC model to detect implicit emotions in written text, outperforming the lexicon-matching method. However, these methods had lower accuracy than machine learning methods. Some researchers have combined scientific annotation based on the OCC model with machine learning methods. Liu and Qi (2018) performed a fine-grained emotion annotation for sentiment analysis using the OCC model and compared five machine learning models. The Logistic Regression model performed the best. Wu et al. (2020) built a sentiment classification rule library based on the OCC model to annotate Weibo opinions, which improved the accuracy of sentiment classification models. However, the manual annotation based on the OCC model is time-consuming, making these methods inefficient. Therefore, a hybrid model that combines automatic emotion reasoning and enhanced machine learning methods is needed to improve sentiment analysis.

2.3. Hybrid approaches to sentiment analysis

Hybrid approaches to sentiment analysis that combine knowledge-based techniques and machine-learning methods have shown promising results in improving classification accuracy (Cambria et al., 2017). Some studies have improved the performance of machine learning methods by incorporating sentiment lexicons or knowledge bases. Song et al. (2019) used sentiment lexicon embedding to represent the semantic relation of sentiment words, which improved the performance of attention-based long short-term memory networks for sentiment analysis. Li et al. (2020) improved the proportion of sentiment information in each review by using a sentiment lexicon to perform sentiment padding. They also proposed lexicon-integrated two-channel CNN-LSTM family models to improve the performance of sentiment classification. Recently, some researchers have enhanced the feature representation capability of deep neural networks with sentiment knowledge to improve the performance of deep learning in sentiment analysis. Chen and Huang (2019) proposed a knowledge-enhanced neural network framework to improve the performance of deep learning models using sentiment knowledge graphs. The research provided more detailed results and achieved competitive performance with limited training corpora.

With the development of deep learning, incorporating auxiliary knowledge with more advanced deep learning models can achieve better performance in sentiment analysis. BERT is an advanced pre-trained language model that obtains deep bidirectional encoder representations of characters based on masked language models and transformer structures (Devlin et al., 2019; Vaswani et al., 2017). It has achieved excellent performance in sentiment analysis (Geetha & Renuka, 2021; Hoang et al., 2019; Pota et al., 2021; Sousa et al., 2019). Meškelė and Frasincar (2020) used a lexicalized domain ontology to capture domain knowledge and used BERT for word embedding, which is combined with the designed neural attention model to provide a hybrid solution for sentiment analysis. Jain et al. (2023) proposed BERT-DCNN with a sentic knowledge base (Cambria et al., 2010) for sentiment analysis in social media, achieving better results than the original BERT. Jin et al. (2023) introduced a knowledge augmentation framework that leverages descriptive knowledge from the Oxford dictionary to enhance BERT for aspect-based sentiment analysis. Considering that Knowledge Graphs (KGs) contain highly reliable domain knowledge, some scholars have combined BERT and KGs for sentiment classification. Liu et al. (2020) used three Chinese KGs, namely, CN-DBpedia (Xu et al., 2017), HowNet (Dong et al., 2010), and MedicalKG as auxiliary knowledge. They proposed K-BERT, a knowledge-enabled feature representation model, for sentiment classification. Liu et al. (2023) utilized an English lexical database, WordNet (Miller, 1995), to enhance the performance of BERT for aspect-based sentiment analysis. Compared to the aforementioned common-sense KGs, the Sentiment Analysis Knowledge Graphs (SAKGs) can provide highly reliable sentiment knowledge. Yan et al. (2021) used a SAKG for semantic annotation to generate sentence trees, which improves both the interpretability as well as classification accuracy of BERT. Zhao and Yu (2021) proposed a knowledge-enabled BERT that uses a manually constructed SAKG to improve the accuracy of sentiment analysis and compensates for the lack of explainability of BERT as a black box.

While existing hybrid approaches to sentiment analysis effectively use sentiment lexicons, common-sense KGs, or SAKG as auxiliary knowledge to improve deep learning models, certain challenges remain. Firstly, these pieces of auxiliary knowledge face difficulties in identifying the complex and conflicting emotions within the OPOEs. Therefore, there is an urgent need for a dedicated emotion model that can effectively extract emotion knowledge from these complex textual expressions; Secondly, although knowledge-enabled feature representation can avoid the problem of knowledge noise caused by too much knowledge incorporation (W. Liu et al., 2020), it cannot prevent the incorporation of inappropriate emotions from distorting the correct meaning of the original sentence. In particular, OPOEs often contain complex and varied emotions. When the polarity of the incorporated sentiment knowledge does not match the polarity of the OPOEs, it may exacerbate the knowledge noise. Consequently, a selective knowledge incorporation mechanism is required for the knowledge-enabled feature representation model.

3. Research objectives

The objective of this research is to develop a sentiment analysis model, ECR-BERT, that produces accurate and explainable results for OPOEs, which can facilitate a better understanding of public sentiment and crisis management during and after emergency events. To achieve this objective, we aim to address the following Research Questions (RQs):

RQ1: The OCC model is full of complex and ambiguous cognitive-induced conditions, how to perform automatic emotion reasoning?

RQ2: OPOEs often contain complex and diverse emotions, how to choose the inferred emotion-cognitive knowledge that is consistent with the sentiment tendency of OPOEs as auxiliary knowledge?
RQ3: The input turns into a tree structure when the inferred emotion-cognitive knowledge is incorporated, how to capture the structural information of the input and make the use of inferred emotion-cognitive knowledge more efficient?
RQ4: Can ECR-BERT achieve the best classification performance and explain how sentiment polarity is derived from fine-grained emotion categories?

4. Methodology

4.1. Overall architecture

The ECR-BERT model architecture, shown in Fig. 2, consists of two modules: ECR and BERT. The function of the ECR module is to transform an OPOE into a sentence-emotion tree. Specifically, the ECR module infers the emotion-cognitive knowledge (cf., Notation 3 in Section 4.2.1.), including Positive Emotion-Cognitive Knowledge (PECK) and Negative Emotion-Cognitive Knowledge (NECK), from the given OPOE. Then, the proposed self-adaptive fusion algorithm is applied to generate a sentence emotion tree. In the BERT module, we apply the soft-position embedding strategy to embed the sentence emotion tree and use a mask-transformer to extract its semantic information, which allows the emotion-cognitive knowledge to improve the feature representation of the OPOE without directly affecting its original meaning. Finally, the sentiment polarities are predicted by a linear classification layer.

The above process is achieved through a two-stage sentiment understanding. The dashed lines indicate the initial stage, where sentiment understanding is derived from BERT. In this stage, the soft-position embedding and mask self-attention are the same as hard-position embedding and self-attention, since the inputs are OPOEs (cf., Section 4.3.2). In the second stage, emotion-cognitive knowledge is obtained from the ECR. A sentence-emotion tree is then generated by a self-adaptive fusion algorithm that integrates the outputs of both ECR and BERT. At this stage, the soft-position embedding and mask self-attention are applied to acquire feature representation of sentence-emotion trees. This process leads to the culmination of the second stage sentiment understanding. Meanwhile, emotion-cognitive knowledge provides emotion details that serve as explanations for the sentiment analysis.

4.2. Emotion-cognitive reasoning

4.2.1. Summary of notations

To demonstrate our method concisely and clearly, we first summarize several notations involved.

Notation 1. $EDD = \{D_1 : (w_1, \cdots, w_{n_1}), \cdots, D_k : (w_1, \cdots, w_{n_k})\}$ represents an emotion dimension dictionary containing a secondary ontology structure, where D_k is the $k-th$ emotion dimension value, and w_{n_k} is the $n_k - th$ emotion word in D_k. For each emotion word, *EDD* provides corresponding attributes such as sentiment polarity and sentiment intensity.

The emotion dimension values represent cognitive-induced conditions (Huangfu et al., 2013), so we can use *EDD* to identify the emotion words contained in an OPOE and the cognitive-induced conditions that the OPOE satisfies.

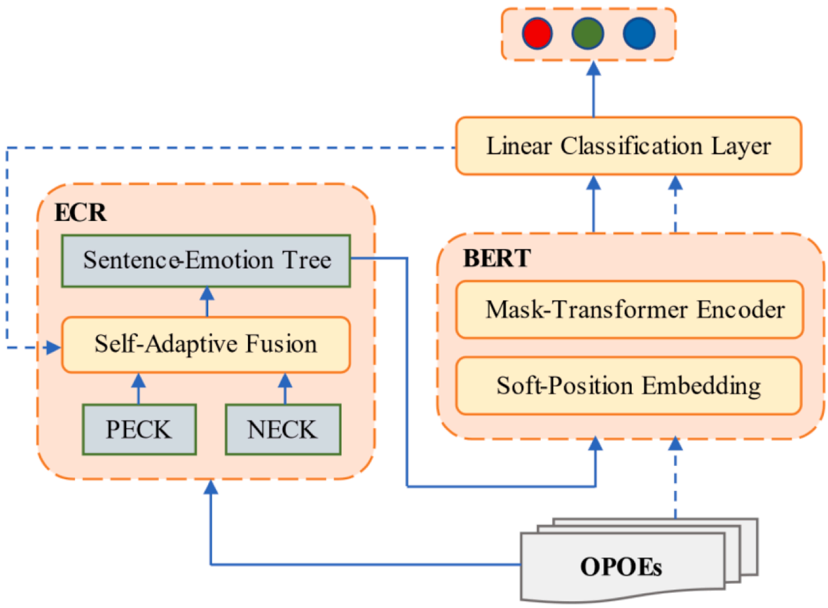

Fig. 2. The overall architecture of ECR-BERT.

Notation 2. $OPOE = \{w_1, \cdots, w_i, \cdots, w_n\}$ represents an online public opinion on emergencies, where w_i is the $i-th$ word in *OPOE*. When w_i is an emotion word, we can use *EDD* to identify the emotion dimension value to which it belongs.

We clarify that an OPOE may consist of one or more sentences and that not all words in an OPOE are emotion words. For simplicity, when performing rule reasoning, we do not consider the order of emotion words in the OPOE, but only the emotion dimension value to which it belongs.

Notation 3. $ECK = \{[w_i, e_i] | w_i \in D_i \in EDD\}$ represents emotion-cognitive knowledge, where w_i is an emotion word, and e_i is an emotion. This means that w_i satisfies the cognitive-induced condition D_i, eliciting e_i. When emotions are elicited by two different cognitive-induced conditions, the *ECK* turns into $ECK = \{[w_i, w_j, e_j] | w_i \in D_i \in EDD, w_j \in D_j \in EDD\}$. In this study, emotions are elicited by at most two cognitive-induced conditions (cf., Section 4.2.2.).

Notation 4. $SET = \{w_1, \cdots, w_i, \cdots, w_j\{[w_i, e_j], \cdots\}, \cdots, w_m\{e_m\}, \cdots, w_n\}$ represents a sentence-emotion tree, where $w_j\{[w_i, e_j], \cdots\}$ and $w_m\{e_m\}$ are the generated *ECK* from an OPOE. SET is the integration of OPOE and ECK, so we can denote the generation of SET as $SET = f(OPOE, ECK)$. To clarify, in the "sentence-emotion tree", the term "sentence" refers to the original OPOE, which can be made up of one or multiple sentences.

For clarity, we provide a summary of the relationships between emotion words, emotion dimension values, cognitive-induced conditions, and emotions contained in the above notations. Emotions are elicited by cognitive-induced conditions, and cognitive-induced conditions can be represented by emotion dimension values (Huangfu et al., 2013). Both emotion words and emotion dimension values make up the emotion dimension dictionary, where each emotion word belongs to a specific emotion dimension value. Therefore, we can achieve automatic emotion reasoning with the help of the emotion dimension dictionary.

Fig. 3 is an example to help understand the above notations. "My wishes are that all medical staff are **healthy**! All the **bastards** who cause **disasters** will be **damned**." This is a Weibo user's opinion during the COVID-19 global pandemic. With the help of the *EDD*, we can identify that "healthy", "bastards", "disasters" and "damned" are emotion words that belong to "Desirable", "Blameworthy", "Undesirable" and "Undesirable", respectively. Based on the knowledge extraction algorithm (cf., Section 4.2.3), we can generate *ECK*: {[bastards, disasters, anger] and [bastards, damned, anger], [healthy, joy]}. Finally, the original OPOE can be converted to a *SET*: {My wishes are that all medical staff are **healthy** {joy}! All the **bastards** {[*disasters, anger*], [damned, anger]} who cause **disasters** will be **damned**.}.

4.2.2. Building emotion-cognitive rules

The OCC model is a tree structure that forms 22 emotion categories based on different contextual conditions related to consequences of events, the actions of agents, and aspects of objects. However, the OCC model is full of complex and ambiguous cognitive-induced conditions, which makes it difficult to perform automatic reasoning. Inspired by the investigation of the inheritance-based emotional logic structure of the OCC model (Steunebrink et al., 2009) and the OCC model-based emotion extraction (Huangfu et al., 2013), we use six emotion dimension values, namely, desirable, undesirable, praiseworthy, blameworthy, confirmed, and disconfirmed, to represent the cognitive-induced conditions as well as to build 10 emotion-cognitive rules. This can simplify the OCC model and enable automatic reasoning. Considering whether the emotions are elicited by multiple cognitive-induced conditions, we classify them as single rules and compound rules. Fig. 4 shows the reasoning paths and emotions inferred by these rules. Gray lines in Fig. 4 indicate that these rules have been constrained to simplify the OCC model.

(1) Single rules

For the "*Desirable*" and "*Undesirable*", we do not consider the case that the consequence is prospective to simplify the OCC model. "*Desirable*" refers to the feeling of being pleased with the actual outcome of an event, eliciting the emotion of "*Joy*" as the inferred

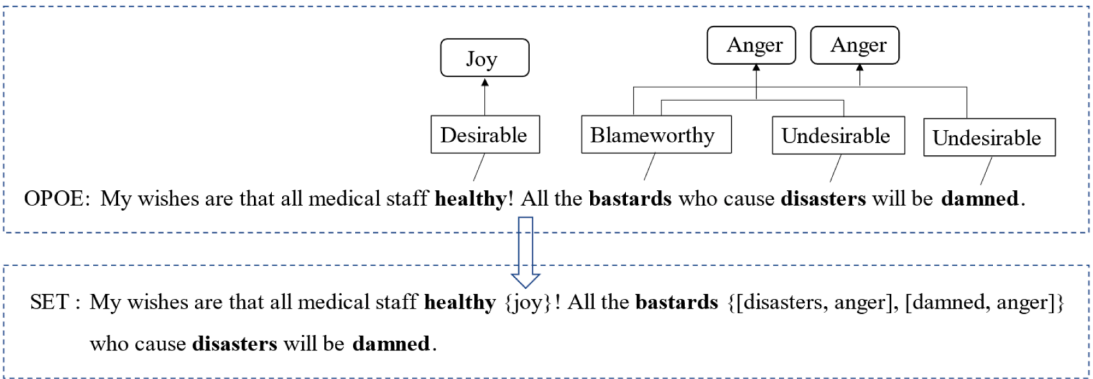

Fig. 3. An example of emotion-cognitive reasoning.

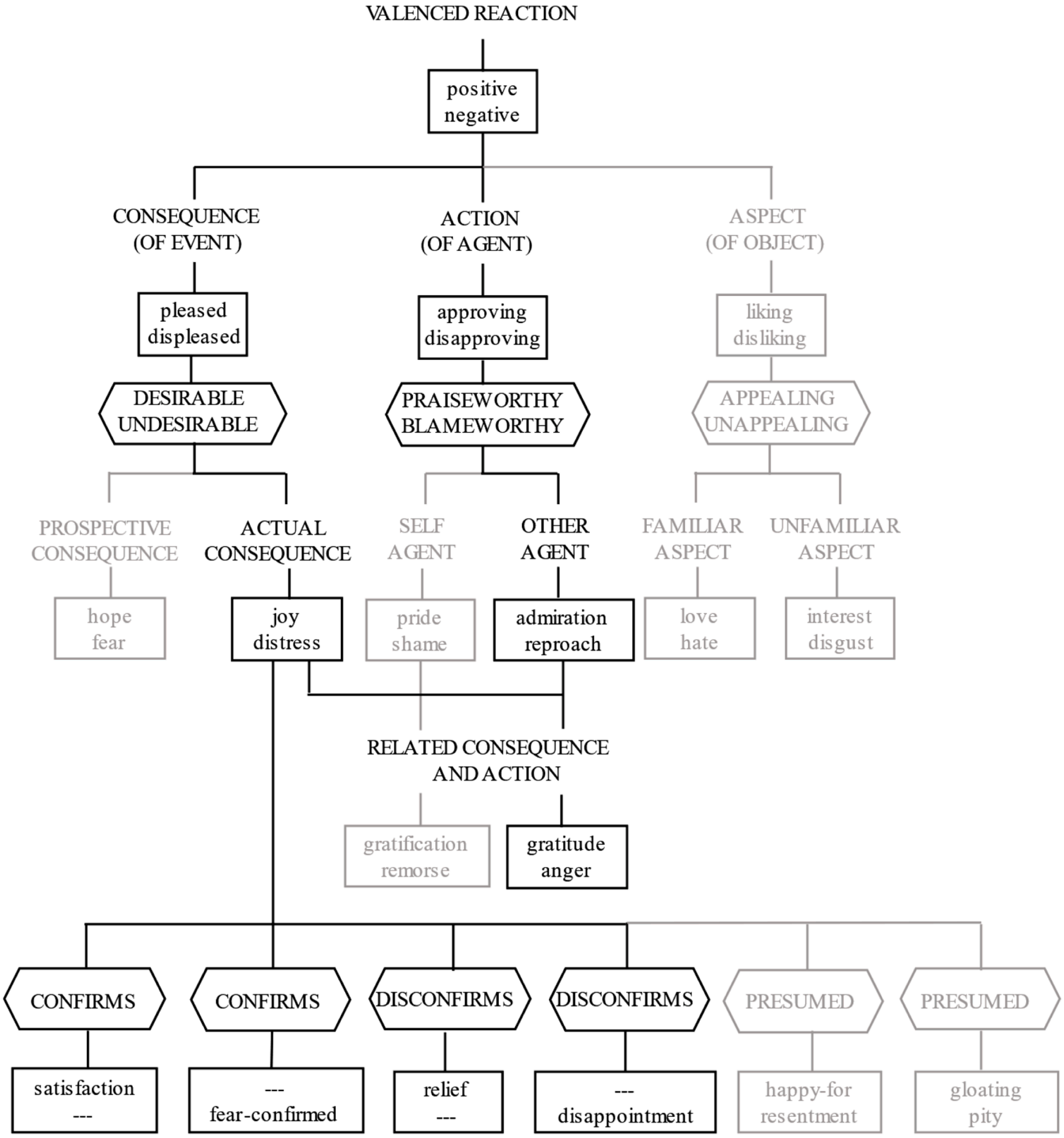

Fig. 4. Inheritance-based emotional logic structure of OCC.

result. Conversely, "*Undesirable*" refers to the feeling of being displeased with the actual outcome of an event, eliciting the emotion of "*Distress*".

$$Emotion(Joy) = DimensionValue(Desirable) \tag{1}$$

$$Emotion(Distress) = DimensionValue(Undesirable) \tag{2}$$

For the "*Praiseworthy*" and "*Blameworthy*", we do not consider the case that the action is for a self-agent to simplify the OCC model. "*Praiseworthy*" denotes approval of someone else's action while "*Blameworthy*" denotes disapproval of someone else's action. These two cognitive-induced conditions elicit "*Admiration*" and "*Reproach*", respectively.

$$Emotion(Admiration) = DimensionValue(Praiseworthy) \tag{3}$$

$$Emotion(Reproach) = DimensionValue(Blameworthy) \tag{4}$$

Rules (1)–(4) infer emotions through a single cognitive-induced condition so they are called "single rules". An example of using a single rule to infer emotion and generate ECK is given here. "**Salute** to the medical staff who are fighting on the front line." is a Weibo user's opinion during the COVID-19 global pandemic. We can observe that "salute" is an emotion word and it belongs to

"Praiseworthy" using the EDD. Based on the rule (3), we can infer the emotion type of admiration and generate ECK: [salute, admiration].

(2) Compound rules

Compound rules suggest the combination of multiple cognitive-induced conditions. Specifically, the combination of "*Desirable*" and "*Praiseworthy*" elicits the emotion of "*Gratitude*". The combination of "*Undesirable*" and "*Blameworthy*" elicits the emotion of "*Anger*".

$$Emotion(Gratitude) = DimensionValue(Desirable) \wedge DimensionValue(Praiseworthy) \tag{5}$$

$$Emotion(Anger) = DimensionValue(Undesirable) \wedge DimensionValue(Blameworthy) \tag{6}$$

Satisfaction, fear-confirmed, relief, and disappointment are seen as specializations of joy/distress when an event has been perceived by the confirmed signals or disconfirmed signals. Therefore, the combination of "*Confirmed*" and "*Desirable*" elicits the emotion of "*Satisfaction*". The combination of "*Confirmed*" and "*Undesirable*" elicits the emotion of "*Fear-confirmed*". The combination of "*Disconfirmed*" and "*Desirable*" causes the emotion of "*Relief*". The combination of "*Disconfirmed*" and "*Undesirable*" causes the emotion of "*Disappointment*".

$$Emotion(Satisfaction) = DimensionValue(Desirable) \wedge DimensionValue(Confirmed) \tag{7}$$

$$Emotion(Fear - confirmed) = DimensionValue(Undesirable) \wedge DimensionValue(Confirmed) \tag{8}$$

$$Emotion(Relief) = DimensionValue(Desirable) \wedge DimensionValue(Disconfirmed) \tag{9}$$

$$Emotion(Disappointment) = DimensionValue(Undesirable) \wedge DimensionValue(Disconfirmed) \tag{10}$$

Rules (5)—(10) infer emotions of two different cognitive-induced conditions so they are called "compound rules". It is noted that "single rules" are considered when the "compound rules" are unable to generate the ECK. As illustrated in Fig. 3, we can first infer the emotion type of anger and generate *ECK*: [disasters, bastards, anger] and [damned, bastards, anger] based on the compound rule (6). Then, we can infer the emotion type of joy and generate ECK: [healthy, joy] based on the single rule (1).

Rules (1), (3), (5), (7), and (9) identify positive emotions such as joy, admiration, gratitude, satisfaction, and relief, and the resulting ECK is therefore positive (i.e., PECK). On the other hand, rules (2), (4), (6), (8), and (10) take into account negative emotions such as distress, reproach, anger, fear-confirmed, and disappointment, so the ECK becomes negative (i.e., NECK). In the above examples, [salute, admiration] and [healthy, joy] are PECK, [disasters, bastards, anger] and [damned, bastards, anger] are NECK.

4.2.3. Knowledge extraction

As the example shown in Fig. 3, OPOEs sometimes mix positive and negative emotion types. To address this issue, we extract PECK and NECK from each OPOE using 10 emotion-cognitive rules. In cases where ECK cannot be extracted from OPOEs, we output "Get no PECK" or "Get no NECK" accordingly. Additionally, we calculate the Emotion Score (ES) to indicate the general sentiment tendency of an OPOE, which also serves as a discriminator for selecting PECK or NECK as auxiliary knowledge to generate SETs.

First, the positive sentiment intensity and negative sentiment intensity of an OPOE are calculated using Eqs. (11) and (12),

Algorithm 1
Knowledge Extraction.

Input: *OPOE, EDD*
Output: *PECK, NECK, ES,* CS_{ECR}

for each *OPOE* **do**
  Identify emotion words in *OPOE* using *EDD* (Notation 1 and Notation 2)
  if emotion words do not exist **then**
    $ES = CS_{ECR} = 0$
    PECK = "Get no PECK"
    NECK = "Get no NECK"
  else
    Calculate *ES,* CS_{ECR} using Eqs. (11)–(14)
    if *ES*=1 **then**
      Generate *PECK* combining Notation 3 and rules (1), (3), (5), (7), (9)
      NECK ="Get no NECK"
    else if =− 1 **then**
      PECK = "Get no PECK"
      Generate *NECK* combining Notation 3 and rules (2), (4), (6), (8), (10)
    else
      Generate *PECK* and *NECK* combining Notation 3 and rules (1)–(10)
    end if
  end if
end for

Algorithm 2
Self-Adaptive Fusion.

Input: *OPOE, PECK, NECK, ES,* CS_{ECR}, CS_{BERT}, *threshold*
Output: *SET* (cf., Notation 4)

```
for each OPOE do
  Calculate ŷ and δ using Eqs. (15)—(20)
  if CS_ECR ≥ threshold then
    if ES > 0 then SET = f (OPOE, PECK)
    else if ES < 0 then SET = f (OPOE, NECK)
    else SET = OPOE
  else
    if δ < 0 then
      if ES > 0 then SET = f (OPOE, PECK)
      else if ES < 0 then SET = f (OPOE, NECK)
      else SET = OPOE
    else
      if ŷ = 0 then SET = f (OPOE, PECK)
      else if ŷ = 1 then SET = f (OPOE, NECK)
      else SET = OPOE
    end if
  end if
end for
```

Fig. 5. Soft-position index.

respectively, as follows:

$$S_P = \sum\nolimits_{i=1}^{n} I\left(w_i^P\right) * F\left(w_i^P\right) \tag{11}$$

where w_i^P is a positive emotion word, $I(w_i^P)$ is emotion intensity of w_i^P, $F(w_i^P)$is the frequency of w_i^P in an OPOE.

$$S_N = \sum\nolimits_{i=1}^{n} I\left(w_i^N\right) * F\left(w_i^N\right) \tag{12}$$

where w_i^N is a negative emotion word, $I(w_i^N)$ is sentiment intensity of w_i^N, $F(w_i^N)$is the frequency of w_i^N in an OPOE.

Then, the ES is calculated using Eq. (13).

$$ES = \frac{S_P - S_N}{S_P + S_N} \tag{13}$$

where $ES \in [-1, 1]$.

$ES > 0$ indicates that OPOE prefers PECK as auxiliary knowledge while $ES < 0$ indicates that OPOE prefers NECK as auxiliary

Table 1
Detailed statistics of the experimental datasets.

Dataset	Positive	Negative	Neutral	Total
COVID-19	6886	3952	2456	13,294
TJ-812	7636	7454	7948	23,038
HZ-Arson	1417	5470	1974	8861
SK-THAAD	5445	5797	5536	16,778

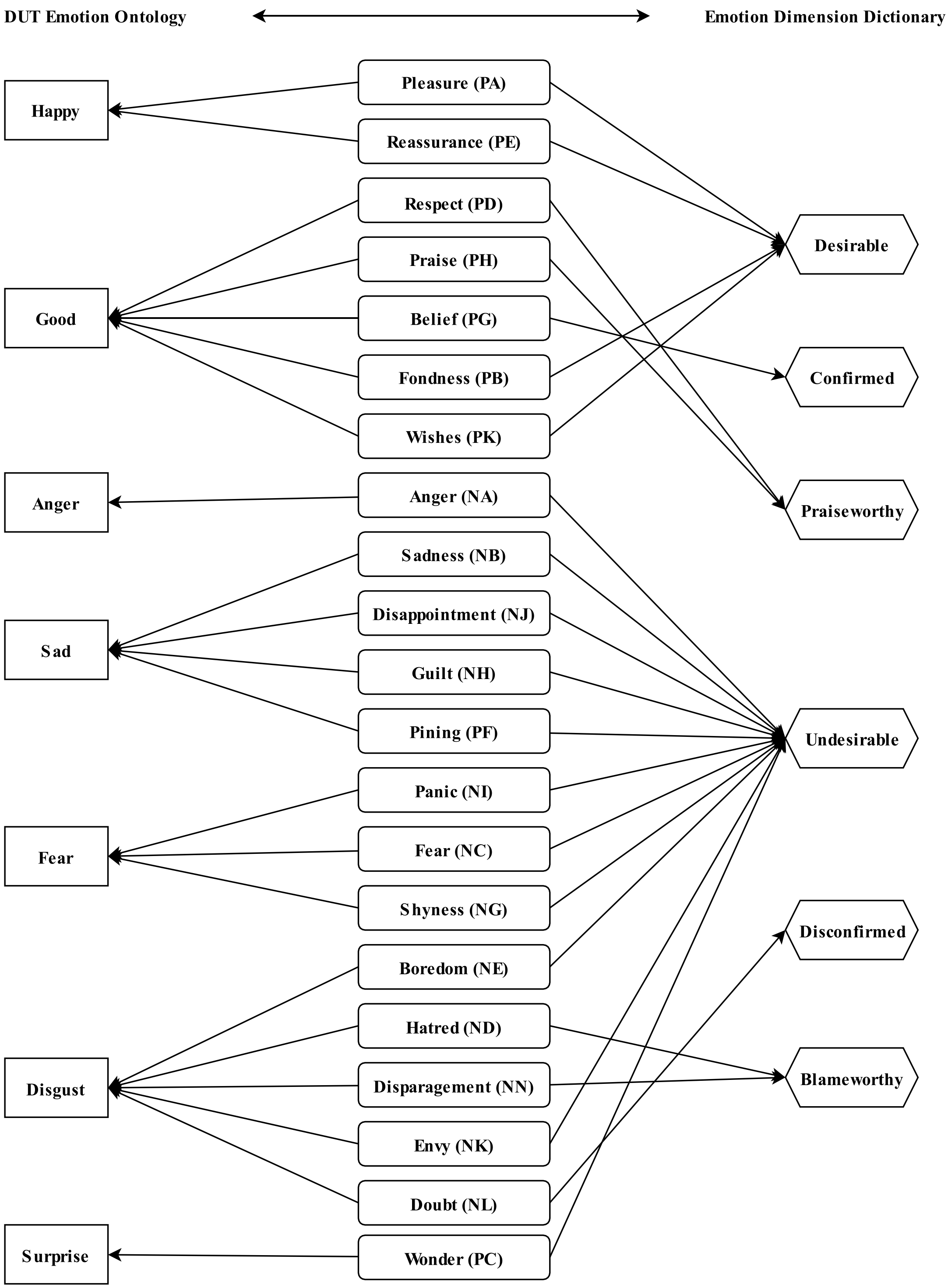

Fig. 6. The consolidation process from the DUT emotion ontology into EDD.

Table 2
Detailed statistics of the EDD.

Emotion dimension	Emotion dimension value	Number of emotion words
Desirability	Desirable	3180
	Undesirable	5167
Confirmation	Confirmed	466
	Disconfirmed	130
Praise-/Blame-worthiness	Praiseworthy	9394
	Blameworthy	9050

Table 3
Parameter setting of models.

Parameters	Value
Fixed length	128
Epoch	10
Dropout rate	0.5
Optimizer	Adam
Batch size	32
Learning rate	2e-5
Threshold	$[0.0, 0.1, \cdots, 1.0]$

Table 4
Performance comparison (%) for different models.

Models \ Datasets	COVID-19		TJ-812		HZ-Arson		SK-THAAD	
	Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1
BERT	84.70	81.45	81.28	81.24	83.27	77.94	86.11	86.04
K-BERT (H)	85.13 ↑0.43	81.95↑0.50	81.87↑0.59	81.86↑0.62	83.84 ↑0.57	78.19↑0.25	86.61↑0.50	86.58↑0.54
K-BERT (C)	84.95 ↑0.25	81.90↑0.45	81.32↑0.04	81.33↑0.09	84.13 ↑0.86	78.39↑0.45	86.48↑0.37	86.42↑0.38
SAKG-BERT	84.82 ↑0.12	81.46↑0.01	81.52↑0.24	81.50↑0.26	83.24 ↓0.03	76.52↓1.42	86.53↑0.42	86.48↑0.44
BERT-DCNN	85.17 ↑0.47	81.73↑0.28	81.88↑0.60	81.87↑0.63	83.90 ↑0.63	77.55↓0.39	86.79↑0.68	86.70↑0.66
ALBERT-TextCNN-Hatt	84.86 ↑0.22	81.59↑0.41	82.25↑0.97	82.26↑1.02	84.00 ↑0.73	78.66↑0.72	86.44↑0.33	86.42↑0.38
ECR-BERT	**85.52 ↑0.82**	**82.31↑0.86**	**83.02↑1.74**	**82.98↑1.74**	**84.25 ↑0.98**	**78.49↑0.55**	**87.48↑1.37**	**87.40↑1.36**

knowledge. When $ES = 0$, we cannot obtain the sentiment tendency of the OPOE.

Finally, the absolute value of the ES reflects the confidence level of the sentiment tendency. We use Confidence Scores (CS) to represent this confidence level (Sazzed & Jayarathna, 2021). To differentiate from the CS of BERT below, we use CS_{ECR} here to denote the CS of ECR.

$$CS_{ECR} = |ES| \tag{14}$$

where $CS_{ECR} \in [0, 1]$.

Algorithm 1 provides the pseudo-codes for knowledge extraction.

4.2.4. Generating sentence-emotion trees

Based on Algorithm 1, we can extract ECK including PECK and NECK from an OPOE and obtain the corresponding ES and CS_{ECR}. ES guides the OPOE to generate a SET by selecting one of the PECK and NECK that is consistent with the sentiment tendency of OPOE. CS_{ECR} provides the confidence level for this selection.

However, the calculation of ES relies on the presence of emotion words, which cannot capture the contextual semantics of an OPOE, resulting in the sentiment tendency that is sometimes incorrect. This means that ES may lead the OPOE to select an ECK that is inconsistent with its real sentiment tendency. Therefore, we proposed a self-adaptive fusion algorithm that integrates the results of ECR and BERT to implement a selection mechanism for the incorporation of knowledge. Specifically, we first use BERT (Devlin et al., 2019) to calculate the sentiment tendency of an OPOE and corresponding CS (i.e., CS_{BERT}). Then, we compare CS_{BERT} with CS_{ECR} and generate SET according to the method with high CS.

Supposing that we have obtained the feature representation of OPOEs through BERT, which will be described in Section 4.3. Here, we focus on how the self-adaptive fusion algorithm is implemented.

First, we use a linear classification layer to predict the sentiment categories of OPOEs.

$$\widehat{Y} = W \times F + b, W \in R^{d \times k} \tag{15}$$

where F denotes the feature vector of an OPOE based on BERT, W denotes the weight vector and belongs to the vector space $R^{d \times k}$, d is

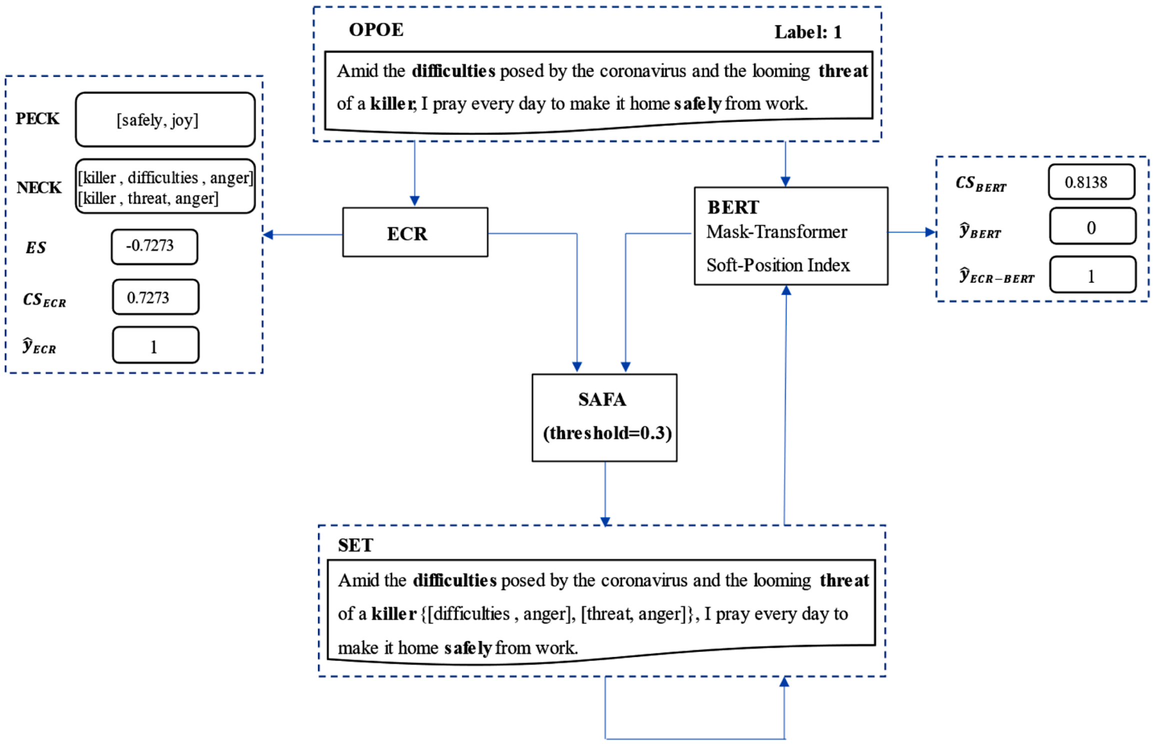

Fig. 7. ECR improves the accuracy and provides explanations.

the dimension of the text feature, k is the number of sentiment categories, $\widehat{Y} = (\widehat{y}_1, \cdots, \widehat{y}_i, \cdots, \widehat{y}_k)$ and $\widehat{y}_i$ denotes the predicted value corresponding to the sentiment category i.

We use the softmax function to normalize $\widehat{y}$.

$$\widehat{y}_i^* = softmax(\widehat{y}_i) = \frac{e^{\widehat{y}_i}}{\sum_{i=1}^{k} e^{\widehat{y}_i}}, \widehat{y}_i \in \widehat{Y} \tag{16}$$

where $\widehat{y}_i^*$ denotes the probability that the sentiment category is i.

Then, we can predict the label of the OPOE and the corresponding CS_{BERT} using Eqs. (17) and (18).

$$\widehat{y} = argmax\left(\widehat{y}_1^*, \cdots, \widehat{y}_k^*\right) \tag{17}$$

$$CS_{BERT} = max\left(\widehat{y}_1^*, \cdots, \widehat{y}_k^*\right) \in (1/k, 1) \tag{18}$$

where $\widehat{y}$ is the predicted label based on BERT. There are three categories (i.e., positive, negative, and neutral) of OPOEs in this study. $\widehat{y} = 0$ indicates the predicted label of OPOE is positive, and PECK will be incorporated into OPOE to generate SET; $\widehat{y} = 1$ indicates the predicted label of OPOE is negative, and NECK will be incorporated into OPOE to generate SET; $\widehat{y} = 2$ indicates that the predicted label of OPOE is neutral, and none of PECK and NECK will be incorporated into OPOE.

Then, we use a Min-Max scaler to normalize CS_{BERT}, which enables the distribution intervals of CS_{ECR} and CS_{BERT} to be the same.

$$N(CS_{BERT})_i = \frac{CS_i - CS_{min}}{CS_{max} - CS_{min}} \in (0, 1) \tag{19}$$

Table 5
The evaluation results of our method in fine-grained sentiment analysis.

Models \ Datasets	COVID-19		TJ-812		HZ-Arson		SK-THAAD	
	HL	F1 (%)	HL	F1 (%)	HL	F1 (%)	HL	F1 (%)
ECR	0.0614	58.01	0.1303	43.36	0.0703	52.34	0.0678	45.07
ECR-BERT	**0.0363**	**62.76**	**0.0502**	**69.65**	**0.0189**	**55.90**	**0.0273**	**53.42**

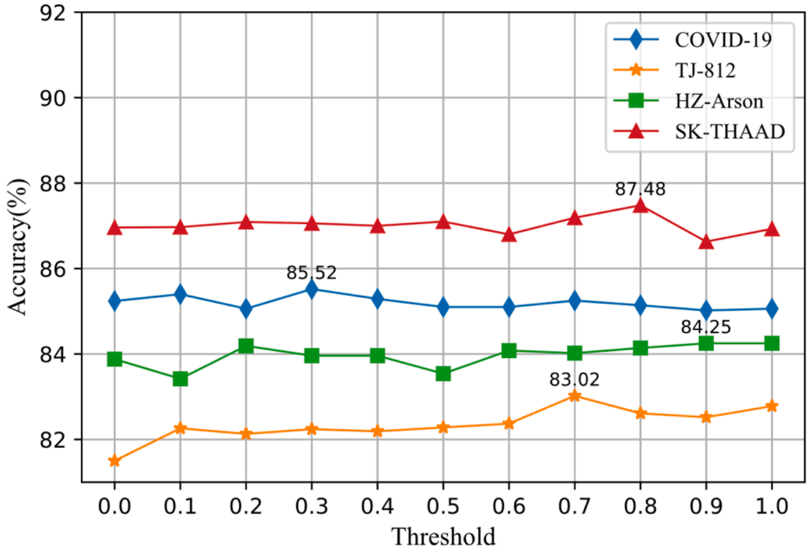

Fig. 8. Performance of different thresholds of ECR-BERT in different datasets.

where $CS_i \in CS_{BERT}$. For simplicity, we do not introduce any new symbols. The CS_{BERT} that appears below denotes the normalized CS_{BERT}.

Finally, we compare CS_{ECR} and CS_{BERT} which determines whether PECK or NECK is incorporated into OPOE.

$$\delta = CS_{BERT} - CS_{ECR} \tag{20}$$

where δ is the comparison result.

Eq. (20) determines the result of the incorporation of knowledge. However, CS_{ECR} and CS_{BERT} are calculated with different formulas, which may lead to different distributions of CS for the two methods. Since BERT has higher prediction accuracy than ECR, we can foresee that CS_{BERT} is larger than CS_{ECR} most of the time. A direct comparison of CS_{BERT} and CS_{ECR} would lead to the incorporation of knowledge favoring the results of BERT. Therefore, we set a threshold in the self-adaptive fusion algorithm to correct this effect.

The threshold serves as a hyper-parameter that ranges from 0 to 1, representing the priority level of ECR. If the CS_{ECR} is greater than the threshold, the incorporation of knowledge is performed directly based on the results of ECK. When the threshold is close to 1, only a small number of CS_{ECR} can exceed the threshold, which means that ECR has a low priority. When the threshold is close to 0, most of CS_{ECR} are above the threshold, which means that ECR has a high priority. In particular, when the threshold is 0, the incorporation of knowledge is based only on the results of ECR. In real-life applications, we need to choose the appropriate threshold to yield the optimal result.

It should be noted that the threshold applied in this study pertains to the entire dataset, not to an individual OPOE. Consequently, the incorporated ECK may exhibit inconsistency with the predictive outcomes of ECR-BERT for a given OPOE. Therefore, we employ an ECK that aligns with the final predictive results of ECR-BERT to provide fine-grained emotion categories as explanations for the predicted polarity of sentiment.

Algorithm 2 presents the pseudo-codes for self-adaptive fusion.

4.3. Knowledge-enabled feature representation

Google's BERT has a limitation in capturing the structural information of input SETs (Devlin et al., 2019). To overcome this, we modify its position embedding and self-attention blocks for knowledge-enabled feature representation, inspired by (W. Liu et al., 2020).

4.3.1. Soft-position embedding

As the gray index in Fig. 5, Google's BERT uses hard-position embedding to represent the token order of input sentences. However, since the SET is a tree structure that incorporates ECK as branches into an OPOE, hard-position embedding makes the SET unreadable and loses its structural information. Therefore, we use soft-position embedding to locate sequence tokens of OPOEs and ECK. As the red index in Fig. 5, we set the consecutive position number for an OPOE and set the same position number for the embedded ECK. For example, we set the number of positions for "disasters" and "damned" in ECK and "who" in the OPOE to 13. When multiple ECKs are incorporated into a node, we set these ECKs to the same position number. For example, the position number of [bastards — disasters — angry] and [bastards — damned— angry] are both set to [12 — 13 — 14]. As (W. Liu et al., 2020), we limit the incorporation of ECK to a maximum of two per node, as excessive ECK integration may cause a divergence from the intended meaning of OPOEs.

Table 6
The consistency of the inferred emotions and the human-identified emotions.

OPOEs	Inferred emotions	Human-identified emotions
Case 1: It is necessary to wear a mask as it is **really scary**.	scary, really → fear-confirmed	fear-confirmed
Case 2: This pandemic is more **severe** than what has been reported so far.	severe → reproach	fear
Case 3: **Salute** to the medical staff who are fighting on the front line.	salute→ admiration	admiration
Case 4: Upon seeing that Weibo and TikTok are filled with news about COVID-19, I feel **anxious**.	anxious → distress	distress
Case 5: We will always be with you.	no emotions	love
Case 6: As a Chinese, you can choose to **believe** any statement, but at this moment, please do not "spread" unverified information, and do not create more panic. It is the basic quality and **kindness**. Some people **question** that they cannot see the situation of all hospitals and doctors in Wuhan, but who is not working hard to fight against the epidemic on the front line? I also want to know, but I also know that **satisfying** my needs at this moment is not the most important thing.	satisfying, question → relief; satisfying, believe → satisfaction; kindness, satisfying → gratitude	relief; satisfaction; gratitude

However, the same position number between OPOE and ECK raises another problem: the position number of "disasters", "damned" and "who" are all 13, which means they are closely related in the calculation of self-attention. But in fact, there is no connection between them. The mask-transformer can solve this problem by limiting the self-attention region, which will be discussed in the next subsection.

4.3.2. Mask-transformer encoder

We use the mask-transformer (W. Liu et al., 2020) for the feature representation of SETs to avoid semantic changes in the original OPOEs caused by emotion-cognitive knowledge branches. The difference between the mask-transformer and Google's transformer (Vaswani et al., 2017) is that the mask-transformer uses a visible matrix to extend the self-transformer (i.e., mask self-attention). The visible matrix is defined as

$$M_{ij} = \begin{cases} 0, & w_i \ominus w_j \\ -\infty, & w_i \oslash w_j \end{cases} \tag{21}$$

where $w_i \ominus w_j$ indicates that w_i and w_j are in the same branch while $w_i \oslash w_j$ are not, i and j are the hard-position index.

M can effectively prevent the risk of semantic changes from auxiliary knowledge injection into the OPOEs by limiting the self-attention region. Accordingly, mask self-attention is defined as

$$Q^{i+1}, K^{i+1}, V^{i+1} = h^i W_q, h^i W_k, h^i W_v \tag{22}$$

$$S^{i+1} = softmax\left(\frac{Q^{i+1} K^{i+1^{\mathrm{T}}} + M}{\sqrt{d_k}}\right) \tag{23}$$

$$h^{i+1} = S^{i+1} V^{i+1} \tag{24}$$

where h^i is the state of the $i-$th hidden layer, d_k is the scaling factor, and S^{i+1} is the attention score. W_q, W_k, W_v are the model parameters.

When no ECK is injected into the OPOEs (i.e., SET $=$ OPOE), we can know that hard-position embedding and soft-position embedding are the same. Meanwhile, mask self-attention and self-attention are the same because the visible matrix is a 0 matrix. In other words, knowledge-enabled BERT and Google's BERT are the same when the inputs are OPOEs. Consequently, we can obtain the feature representation of OPOEs in this scenario. This also explains why we can use OPOEs as inputs shown by the dashed path in Fig. 2, to perform the self-adaptive fusion algorithm.

4.4. Model prediction

After the feature representation of SET is obtained, we use a linear classification layer (cf., (15)—(17)) to predict the sentiment polarity.

Finally, we use the cross-entropy loss as the optimization objective to train the model:

$$L = -\frac{1}{N}\sum_{i=1}^{N} y_i * \log(\sigma(\hat{y}_i)) \tag{25}$$

where N is the number of training samples. y_i is the real label of $i-th$ sample, $\hat{y}_i$ is the predicted value of $i-th$ sample. σ is the softmax function (cf., Eq. (18)).

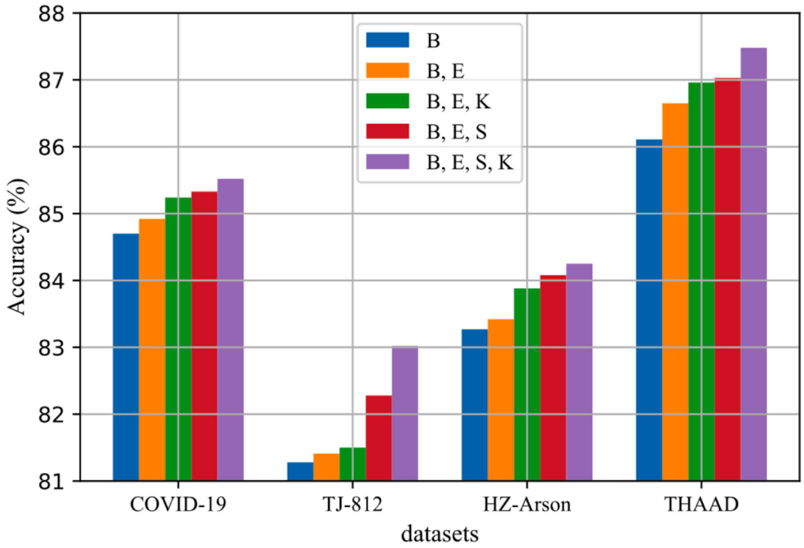

Fig. 9. Comparison of the performance of the different techniques.

5. Experimental results and evaluation

5.1. Dataset

We use four currently the most authoritative and publicly available OPOE sentiment analysis datasets to evaluate our method. The first dataset is from SMP2020-EWECT[1] (i.e., COVID-19), which is an OPOE dataset on COVID-19 that contains six categories: happy, angry, fearful, sad, surprised, and neutral. We converge these into three categories: positive (happy), negative (angry, fearful, and sad), and neutral. The others are from (Wu et al., 2020), which contain three categories: positive, negative, and neutral. These three datasets are OPOE datasets about the "Tianjin explosion accident (i.e., TJ-812)", "Arson case committed by a housekeep in Hangzhou (i.e., HZ-Arson)", and "Deployment of THAAD in South Korea (i.e., SK-THAAD)", respectively. We randomly divide four datasets into a training set (70%), a validation set (10%), and a testing set (20%). Detailed statistics of the four datasets are shown in Table 1.

5.2. Construction of the EDD

We construct the EDD based on the Dalian University of Technology (DUT) emotion ontology, which is a rich and reliable lexicalized ontology resource containing seven emotion categories, 21 subcategories, and 27,466 emotion words (Xu et al., 2008). Each emotion word has different attributes such as subcategory, sentiment intensity, etc. Emoticons are a good indicator of a netizen's emotional state and almost always convey the underlying emotion (Alharbi & de Doncker, 2019). Therefore, we also include 42 common Weibo emoticons in the DUT emotion ontology.[2]

Based on the semantics of the subcategories, we consolidate 21 subcategories of the DUT emotion ontology into the six emotion dimension values of the EDD. Specifically, pleasure (PA), reassurance (PE), fondness (PB), and wishes (PK) are consolidated into the "Desirable"; respect (PD) and praise (PH) to the "Praiseworthy"; belief (PG) to the "Confirmed"; anger (NA), sadness (NB), disappointment (NJ), guilt (NH), pining (PF), panic (NI), fear (NC), shyness (NG), boredom (NE), envy (NK) and wonder (PC) to the "Undesirable"; doubt (NL) to the "Disconfirmed"; and hatred (ND) and disparagement (NN) to the "Blameworthy". Fig. 6 presents this consolidation process. Some emotion words in the DUT emotion ontology are classified into different subcategories, which may correspond to different emotion dimension values, and we consolidate them into one sentiment dimension value. For example, the "reluctant part" belongs to both fondness (PB) and pining (PF), and the corresponding emotion dimension values are "Desirable" and "Undesirable", respectively. We only keep it in "Desirable". The detailed statistics of the EDD are presented in Table 2.

5.3. Baselines

Sentiment analysis of OPOEs is a sentence-based sentiment classification task, we select the following SOTA sentiment analysis models as baselines and compare the performance of our model against these baseline models.

BERT (Devlin et al., 2019): BERT is an advanced pre-trained linguistic model. The pre-trained BERT with a linear classification

[1] https://smp2020ewect.github.io/

[2] https://github.com/StudentxWan/DUT-emotion-ontology-with-emoticons

layer is fine-tuned using labeled data for sentiment analysis.

K-BERT (W. Liu et al., 2020): Knowledge triples from CN-DBpedia (B. Xu et al., 2017) and HowNet (Dong et al., 2010) are injected into sentences to generate sentence trees, soft-position embedding and mask self-attention are proposed for the feature representation. In this study, K-BERT (C) means that CN-DBpedia is used as the domain knowledge base and K-BERT (H) means that HowNet is used as the domain knowledge base.

SAKG-BERT (Yan et al., 2021): Sentiment knowledge triples from SAKG are injected into original texts to help generate sentence trees, and the pre-trained BERT with a linear classification layer is fine-tuned using the sentence trees for sentiment analysis.

BERT-DCNN (Jain et al., 2023): Sentic vectors are generated from sentences by the sentic knowledge base (Cambria et al., 2010), which provides concept-level sentiment information for deep neural networks. BERT-based Dilated Convolutional Neural Network (DCNN) stacked with a global average pooling layer helps in fine-tuning the model to extract sentiment features.

ALBERT-TextCNN-Hatt (Zhang & Ma, 2023): To achieve low memory usage, ALBERT is applied as the backbone model. Topic knowledge acquired through the latent Dirichlet allocation is employed to detect implicit sentiment. The feature reduction is performed using a text convolution neural network, while a hierarchical attention mechanism is used for attention modeling.

Among the above models, K-BERT, SAKG-BERT, BERT-DCNN, and ALBERT-TextCNN-Hatt are all hybrid models that use KGs, sentic knowledge base, and topic knowledge as auxiliary knowledge, while BERT does not use auxiliary knowledge. Our model, ECR-BERT, is also a hybrid model that uses emotion-cognitive knowledge as auxiliary knowledge and uses a self-adaptive fusion algorithm to perform selective knowledge incorporation.

5.4. Experimental setup

To ensure a fair comparison, we set the same parameters for the backbone (i.e., BERT) of all models, where the learning rate setting follows the suggestions from (Yan et al., 2021). For our proposed ECR-BERT, we set the threshold between 0 and 1 with the interval 0.1 and select the best threshold. The detailed parameter settings are shown in Table 3. For BERT-DCNN and ALBERT-TextCNN-Hatt, some additional parameters such as the number of neurons, dilation filter size, dilation width, and convolution kernel size are set according to (Jain et al., 2023; Zhang & Ma, 2023). In addition, we monitor the change of the loss value on the validation set during the training, and the model will automatically stop training if it exceeds one epoch without further improvement.

The selected pretrained BERT[3] and ALBERT[4] models are obtained from the UER platform (Z. Zhao et al., 2019). We then perform pre-training on these models for 5000 steps, using the experimental datasets. The result of this pre-training process serves as our customized pretrained models. The neural network framework is Pytorch 1.10, and the GPU we use is Tesla V100 (32G). For each model, we run it 5 times at random and report the average performance.

5.5. Performance analysis

Consistent with previous work (Chen & Huang, 2019), we use accuracy (Acc.) and micro-F1 (F1) to evaluate the sentiment classification performance of the models. The main results are presented in Table 4. The percentages shown in the rows of Table 4 refer to the percentage improvement of the hybrid models over BERT.

In this experiment, the hybrid models generally outperform BERT in terms of accuracy and micro-F1. The main reason is that the hybrid models utilize auxiliary knowledge to improve the feature representation of BERT. Though HowNet contains much fewer triples than CN-DBpedia (W. Liu et al., 2020), K-BERT (H) outperforms K-BERT (C). This is because HowNet contains the semantic knowledge of Chinese words, which is more helpful for sentiment analysis, while CN-DBpedia contains open-domain encyclopedic. This suggests that the content of the auxiliary knowledge plays a more important role in the performance of K-BERT. BERT-DCNN, which incorporates sentic knowledge (Cambria et al., 2010), uses different dilation rates to capture long-term dependencies, and it performs better than K-BERT (H). Different from K-BERT, ALBERT-TextCNN-Hatt, and BERT-DCNN, SAKG-BERT utilizes sentiment knowledge triples as auxiliary knowledge to improve BERT. Though SAKG as a sentiment knowledge base provides higher quality sentiment knowledge and much richer sentiment features than a domain-specific knowledge base, SAKG-BERT performs worse than K-BERT (H). There exist two reasons: (1) Sentiment knowledge triples contain positive and negative categories, and these triples are injected into the original OPOEs without selection, causing a knowledge noise problem. (2) SAKG-BERT utilizes Google's BERT as the backbone, which cannot capture the structural information of sentence trees. In addition, we found that these models performed differently on the HZ-Arson dataset, with ALBERT-TextCNN-Hatt performing better on the TJ-812 dataset and the HZ-Arson dataset. This suggests that the performance of these models is also influenced by the dataset used.

As shown in the bold results, our proposed ECR-BERT achieves the best performance on four datasets. Furthermore, the T-test results show that the absolute performance improvement of our model over BERT is significantly higher than that of the other hybrid models (p-value of 0.0015, 0.0004, 0.0003, 0.0015, 0.0041, respectively). This is because our model uses extracted ECKs as auxiliary knowledge and uses a self-adaptive fusion algorithm to perform selective knowledge incorporation to generate SETs. In addition, both soft-position embedding and mask self-attention are used to make the use of inferred ECKs more efficient. Fig. 7 shows an example of how our model enhances BERT effectively and provides the fine-grained emotion categories as detailed explanations of the results: "Amid the **difficulties** posed by the coronavirus and the looming **threat** of a **killer**, I pray every day to make it home **safely** from

[3] https://share.weiyun.com/FR4rPxc4

[4] https://share.weiyun.com/DgRASb0k

work." is an OPOE on COVID-19 that contains opposite emotions. This causes BERT to make an incorrect prediction. Algorithm 1 extracts both PECK and NECK. Because CS_{ECR} is greater than the threshold, NECK is incorporated into the OPOE according to Algorithm 2. The generated SET as an input to BERT not only produces a correct prediction but also shows how "negative" is derived from the fine-grained emotion categories (i.e., {[*killer, difficulties→anger→negative*], [killer, threat→anger→negative]}). This case also shows the process by which the self-adaptive fusion algorithm performs selective knowledge incorporation to reduce the knowledge noise (i.e., [safely, joy]).

We evaluate the performance of our method in fine-grained sentiment analysis. To achieve this, we invite three students to perform human annotations guided by the emotion-cognitive rules. In cases where conflicts arise in the annotations, the final results are determined by a consensus vote among these three students. Since an OPOE can contain multiple emotion categories, we use Hamming Loss (HL) and F1-measure (F1) as our chosen evaluation metrics (Sorower, 2010). The results of this evaluation are shown in Table 5.

The results presented in Table 5 clearly show that ECR-BERT significantly outperforms ECR. This is because ECR as a rule-based method has difficulty in semantic understanding, and therefore performs poorly in obtaining positive or negative emotion-cognitive knowledge. In contrast, ECR-BERT combines the outputs of both ECR and BERT, giving it a significant advantage in understanding the sentiment trends within OPOEs. This, in turn, assists ECR in deriving emotion categories that match the sentiment tendencies of OPOEs. As a result, ECR-BERT significantly enhances the capabilities of ECR, particularly in the area of fine-grained sentiment analysis.

Fig. 8 shows the performance of ECR-BERT by the self-adaptive fusion algorithm with different thresholds. We can observe that the optimal threshold varies for different datasets. This is because the thresholds balance the impact of ECR and BERT on the incorporation of knowledge, and the performance of ECR and BERT may differ for different datasets, leading to variations in the optimal threshold. This indicates that for any OPOE dataset, regardless of the performance of ECR, the self-adaptive fusion algorithm can always select the appropriate threshold to ensure that our model achieves the best classification performance. In real-life applications, we can set several thresholds ranging from 0 to 1 with the same interval to obtain the best results for the different datasets.

5.6. Qualitative analysis

We perform a qualitative analysis to verify the consistency between the inferred emotions and the human-identified emotions. Table 6 presents several typical cases.

As shown in Table 6, the inferred emotions demonstrate consistency when compared to the human-identified emotions in Cases 1, 3, 4, and 6. However, there are some differences in Cases 2 and 5, indicating certain imperfections in the reasoning process. For example, the OPOE "This pandemic is more severe than what has been reported so far." is inferred to express a reproach emotion, because the word "severe" falls under the "blameworthy" emotion dimension value identified by EDD. However, as humans, we tend to feel a sense of fear. This is because the ECR uses simplified emotion-cognitive rules, which means that the emotions inferred are not exactly precise. Another example is the OPOE "We will always be with you.", which makes us humans feel a sense of love. However, no emotions are inferred from this OPOE because it does not contain any emotion words. From the above qualitative analysis, we can conclude that our model can provide fine-grained emotions as explanations when an OPOE contains emotion words, and the outputs from our models are generally consistent with the human-identified emotions.

5.7. Ablation study

In this section, three additional experiments were conducted to further explore the contributions of different techniques. B, E, K, and S stand for BERT, ECR, Knowledge-enabled feature representation, and the Self-adaptive fusion algorithm, respectively.

"B, E" denotes the combination of BERT and ECR, where both PECK and NECK are incorporated into OPOEs to generate SETs and Google's BERT with a linear classification layer is fine-tuned using the SETs. "B, E, K" denotes that we use the knowledge-enabled feature representation instead of Google's BERT compared to "B, E". "B, E, S" denotes that we use the self-adaptive fusion algorithm to perform selective knowledge incorporation to generate SETs compared to "B, E". "B, E, S, K" denotes our proposed ECR-BERT.

The results of the ablation study in Fig. 9 show that "B, E" performs better than BERT but worse than "B, E, K". This indicates that ECK generated by ECR as auxiliary knowledge improves the performance of the BERT and knowledge-enabled feature representation further improves "B, E" due to better feature representation learning. In addition, "B, E, S" outperforms "B, E" and "B, E, K". This indicates that the self-adaptive fusion algorithm improves the use of knowledge through a selection mechanism and improves more than knowledge-enabled feature representation, effectively mitigating the knowledge noise problem. "B, E, S, K" achieves the best performance. This is because "B, E, S, K" combines all technologies and thus achieves the most improvement. The results of this ablation study indicate the effectiveness of each technique and our proposed self-adaptive fusion algorithm helps more than knowledge-enabled feature representation in alleviating knowledge noise and improving the use of knowledge.

6. Discussion and implications

In this section, we discuss the main innovations of this paper by comparing our method to the existing works. We then highlight the theoretical and practical implications.

6.1. Discussion

This paper proposes ECR-BERT, a hybrid model that combines the OCC model with BERT to address four RQs. We simplify the emotion-cognitive rules and present a knowledge extraction algorithm that automatically infers emotion-cognitive knowledge, which answers RQ1. We propose the self-adaptive fusion algorithm for selective knowledge incorporation to address RQ2. Additionally, we adopt knowledge-enabled feature representation to capture the structural information of SETs and make the use of inferred knowledge more efficient, which answers RQ3. Finally, our model achieves high accuracy and provides detailed explanations of how the sentiment is derived from the fine-grained emotion categories, which provides a positive answer to RQ4.

In comparison to (Zhang & Ma, 2023) which uses topic knowledge to enhance sentiment analysis performance, this study utilizes inferred emotion-cognitive knowledge as auxiliary knowledge and proposes a self-adaptive fusion algorithm to mitigate the knowledge noise problem caused by conflicting emotions. This approach results in more accurate prediction results and provides fine-grained emotion categories as explanations.

Similar to (Wu et al., 2020), our research uses the OCC model to improve the accuracy of deep neural networks. Furthermore, we make some improvements to (Wu et al., 2020): (1) we implement automatic reasoning to solve the inefficiency of manual annotation; (2) we use advanced BERT as the backbone model; (3) our model provides detailed explanations of the results.

As per (Chen & Huang, 2019; W. Liu et al., 2020; Yan et al., 2021; A. Zhao & Yu, 2021), we have proposed a knowledge-enhanced deep learning model with several improvements. These said studies require the construction of sentiment analysis knowledge graphs for the dataset. In addition, because they lack a selection mechanism for the incorporation of knowledge, they cannot alleviate the knowledge noise problem due to inappropriate knowledge incorporation. Our research uses a generic emotion ontology to construct EDD and builds emotion-cognitive rules to achieve automatic reasoning, which improves the generalization of the model. In addition, our research proposes a self-adaptive fusion algorithm for selective knowledge incorporation to mitigate the problem of knowledge noise, thereby improving the accuracy of our proposed model.

Although ECR has some limitations, it has proven to be a valuable technique for enhancing BERT. On the one hand, while we use simplified emotion-cognitive rules to infer emotion-cognitive knowledge, the fine-grained emotions inferred may exhibit some inconsistencies with human-identified emotions. However, emotion-cognitive knowledge still serves as useful auxiliary knowledge for improving BERT, as the self-adaptive fusion algorithm provides a selection mechanism to choose either PECK or NECK in accordance with the sentiment tendency of OPOEs. Despite the imprecision of the inferred emotions, the selected one still provides emotional semantic features that are consistent with the sentiment tendency of the OPOEs, thereby enhancing BERT. On the other hand, ECR relies on the presence of emotion words, and thus cannot recognize the emotion dimension values in cases where an OPOE lacks such words. As a result, ECR may be ineffective and unable to provide fine-grained emotions. Nevertheless, our model leverages OPOEs that do contain emotion words and generates SETs to improve the feature representation of BERT, ultimately achieving better performance than BERT. However, this does not imply that precise and effective reasoning is unimportant, and it can be improved in future research.

6.2. Implications

Our study delves into the interdisciplinary realm of cognitive psychology and computer science, offering a fresh perspective for research in sentiment analysis. Furthermore, as an upstream of crisis management research, our research provides an effective method to achieve more accurate classification results and provides detailed explanations of how the sentiment polarity is derived from fine-grained emotion categories. Such efforts are conducive to promoting the development of explainable artificial intelligence. Moreover, we introduce a self-adaptive fusion algorithm, a selective knowledge incorporation algorithm, which contributes an effective solution to mitigate the knowledge noise problem.

Our research provides a novel and practical method for predicting the sentiment polarity of OPOEs, resulting in more accurate and detailed results. This helps emergency responders to develop an accurate and comprehensive sentiment awareness, improving the government's management of crises to promote social harmony.

7. Conclusion and future work

This study combines an emotion model and deep learning to construct ECR-BERT for explainable sentiment analysis of OPOEs, which not only achieves the best classification performance but also provides a detailed explanation of how sentiment polarity is derived from fine-grained emotion categories. It provides a new research perspective for sentiment analysis research. Specifically, we build emotion-cognitive rules and use EDD to achieve automatic reasoning, and we adopt knowledge-enabled feature representation to make the use of inferred knowledge more efficient. Furthermore, we propose a self-adaptive fusion algorithm to perform selective knowledge incorporation, which effectively mitigates the knowledge noise problem. The ablation study shows that the self-adaptive fusion algorithm goes beyond knowledge-enabled feature representation in alleviating knowledge noise and improving the use of knowledge. The experimental results on four open OPOE datasets show that ECR-BERT achieves the best performance. Our study, which combines cognitive psychology and computer science, provides a novel approach to sentiment analysis research and contributes to the development of explainable artificial intelligence. In addition, our research has important practical applications, improving crisis management and response capability, as well as promoting social harmony.

We have a limitation in that we use the simplified emotion-cognitive rules and ECR relies on the presence of emotion words. For future research, we could improve the performance of ECR by considering more emotion dimension values to design emotion-cognitive rules and identifying the emotion words using semantic matching methods.

CRediT authorship contribution statement

Bingtao Wan: Conceptualization, Methodology, Software, Writing – original draft. **Peng Wu:** Methodology, Supervision, Funding acquisition. **Chai Kiat Yeo:** Conceptualization, Supervision. **Gang Li:** Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I have shared the link to my data/code in my paper.

Acknowledgments

This paper was supported by the National Natural Science Foundation of China (project numbers are 72274096, 71774084, 72301136, and 72174087), the Foreign Cultural and Educational Expert Program of the Ministry of Science and Technology of China (G2022182009L).

Appendix

List of abbreviations	
BERT	Bidirectional Encoder Representations from Transformers
CS	Confidence Score
DUT	Dalian University of Technology
ECK	Emotion-Cognitive Knowledge
ECR	Emotion-Cognitive Reasoning
EDD	Emotion Dimension Dictionary
ES	Emotion Score
NECK	Negative Emotion-Cognitive Knowledge
OCC	Ortony, Clore, and Collins
OPOE	Online Public Opinions on Emergencies
PECK	Positive Emotion-Cognitive Knowledge
RQ	Research Question
SAKG	Sentiment Analysis Knowledge Graph
SET	Sentence-Emotion Tree
SOTA	State-of-the-Art

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