

EERPD: Leveraging Emotion and Emotion Regulation for Improving Personality Detection

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Abstract

Personality is a fundamental construct in psychology, reflecting an individual's behavior, thinking, and emotional patterns. While previous researches have made progress in personality detection, their designed methods generally overlook the important connection between psychological knowledge "emotion regulation" and personality traits. Based on this, we propose a new personality detection method called **EERPD**. This method introduces the use of emotion regulation, a psychological concept highly correlated with personality, for personality prediction. By combining this concept with emotion features, EERPD retrieves few-shot examples and provides process CoTs for inferring labels from text. This approach enhances the understanding of LLM for personality implicit within text and improves the performance in personality detection. Experimental results demonstrate that EERPD significantly enhances the accuracy and robustness of personality detection, outperforming previous SOTA by 15.05/4.29 in average F1 on the two benchmark datasets.

1 Introduction

As a fundamental construct in psychology, *personality* reveals the true nature of the individual and creates a certain impression on others (Jung, 1959; Corr and Matthews, 2009; Jung, 1959). With the advancement of Natural Language Processing (NLP) technologies, there has been an growing interest in automatic detection of personality (Petrides and Mavrouli, 2018; Yang et al., 2023), which plays a pivot role in numerous human-oriented NLP applications, such as psychological health assessment (Wilkinson and Walford, 2001), personalized recommendation systems (Hu and Pu, 2010), and human-computer interaction (Pocius, 1991).

Traditional personality detection methods either rely solely on direct content analysis of text with-

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Figure 1: Examples for emotion and emotion regulation sentences. Emotion sentences tend to contain words that are experienced in the short term, while *Emotion Regulation* sentences tend to contain features that are stable in the long term.

out effectively leveraging key psychological concepts (Yang et al., 2023; Hu et al., 2024), or laying particular emphasis on emotion expression (Mohammad and Kiritchenko, 2013; Li et al., 2021). However, these approaches often overlook the role of **Emotion Regulation** (Gross, 2008), a key psychological concept related to personality. Different from emotion that is usually expressed in a short-term manner, emotion regulation is a stable, long-term status of managing and controlling one's emotional responses, as exemplified in Figure 1. Psychological researches have demonstrated a clear correlation between one's personality and emotion regulation (Barańczuk, 2019; Petrides and Mavrouli, 2018; Borges and Naugle, 2017).

Inspired by the psychological studies above, we propose a RAG-based framework named EERPD for automatic detection of personality, leveraging

both emotion and emotion regulation as guidance. To guide the LLMs in personality detection, we first construct a reference library composing of a large number of text-personality pairs. Reference samples most similar to the input text are retrieved to facilitate few-shot learning. To be specific, we categorize each sentence of the input text into emotion sentences and emotion regulation sentences, encode them separately, and then combine the two vectors for effective retrieval of the most similar samples from the reference library. For each retrieved sample, we further include corresponding chain-of-thoughts (CoT) emphasizing emotion and emotion regulation to direct the LLM’s attention to these aspects.

For comprehensive evaluation, we test our EERPD on both the Kaggle dataset ¹ for MBTI (Myers-Briggs, 1991) detection and the Essays dataset (Pennebaker and King, 1999) for the Big Five personality (Goldberg, 1990) detection. The experimental results show that our method significantly improves the few-shot performance of GPT-3.5 in personality detection tasks, outperforming previous SOTA by 15.5/4.3 on average F1 on the two datasets. Further ablation and analysis consolidates the effectiveness of emotion regulation in personality detection, aligning well with psychological discoveries. To sum up, our contributions are as follows:

- To our best knowledge, we are the first to incorporate the *psychological knowledge of emotion regulation* into LLMs for automatic personality detection, going beyond traditional methods that only focus on texts or texts and emotions.
- We propose EERPD, an RAG-based framework that combines *Emotion* and *Emotion Regulation* to improve personality detection. Comprehensive experiments on two benchmarks show that our EERPD outperforms all strong baselines by a large margin.
- We have conducted in-depth analyses to confirm the effectiveness of EERPD, as well as the efficacy of emotion regulation for personality detection.

2 Related Work

Personality Detection In the early development of personality detection, Francis and Booth (1993)

introduced the Linguistic Inquiry and Word Count (LIWC), pioneering the use of psycholinguistic features for personality analysis through texts. This tool became foundational for feature engineering in subsequent studies, such as those by Pennebaker and King (1999) and Argamon et al. (2005), which focused on linguistic styles and lexical predictors of personality traits, achieving moderate accuracies in detecting traits like extraversion and neuroticism.

With the emergence of neural networks, research expanded significantly. Techniques like CNNs and LSTMs enhanced personality prediction from social media (Tandera et al., 2017; Xue et al., 2018a). The introduction of BERT further advanced the field, with Gjurković et al. (2020) showing its effectiveness in analyzing personality and demographics on Reddit without extensive feature engineering.

Recent studies have explored multitask and multimodal approaches to personality detection. Sang et al. (2022) used movie scripts to predict MBTI types of fictional characters, showing the potential of diverse data integration. Li et al. (2021) employed multitask learning to detect emotions and personality traits simultaneously, demonstrating the efficiency of shared representations.

Current research explores large language models (LLMs) for personality detection, as shown by Yang et al. (2023) and Hu et al. (2024), indicating a shift towards inferring personality traits directly from text with minimal reliance on traditional feature engineering and adopting more holistic, context-aware methodologies.

Emotion and Emotion Regulation The relationship between emotion and personality is well studied in psychology and NLP. Psychological theories (Keltner, 1996; Davidson, 2001; Reisenzein and Weber, 2009) link personality traits with emotional experiences, laying the foundation for inferring personality from emotions. Mohammad and Kiritchenko (2013) showed fine-grained emotions enhance personality detection, Rangra et al. (2023) demonstrated the effectiveness of emotional features in speech, and Li et al. (2021) found that multitask learning improves prediction accuracy.

The connection between emotion regulation and personality has also been explored in psychology. Emotion regulation is significantly associated with and can influence personality (Barańczuk, 2019). Individuals with strong emotion regulation skills show personality traits associated with higher job satisfaction and better stress management (Petrides and Mavroveli, 2018). Borges and Naugle (2017)

¹<https://www.kaggle.com/datasnaek/mbti-type>

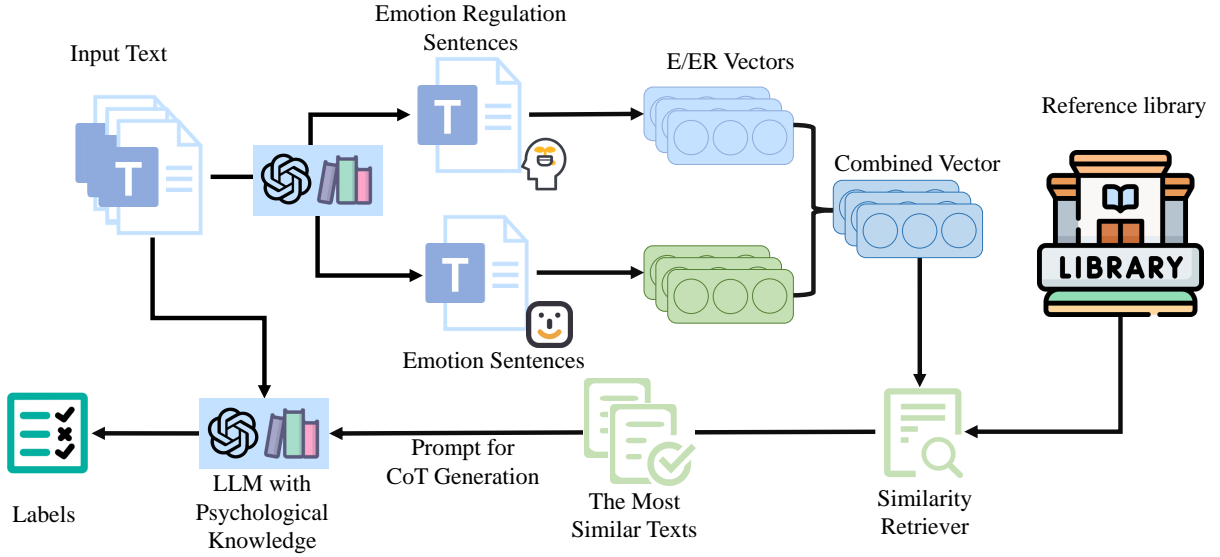


Figure 2: An overall framework of EERPD. The sentences in input text is categorized into Emotion Sentences and Emotion Regulation Sentences, and then are vectorized and proportionally combined. Using the new vectors, we retrieve two examples and generate their corresponding CoT processes. These examples, along with the input text, are then fed into the LLM with psychological knowledge to obtain the final prediction.

found emotion regulation variables predict specific personality dimensions. However, to the best of our knowledge, no NLP-based personality detection methods utilize emotion regulation for prediction.

3 Task Formulation

In this paper, we focus on the personality detection task, which aims to predict an individual’s personality traits from text. Each text to be detected, X , is made up of $\{x_1, x_2, \dots, x_n\}$, where each x_i is a sentence. The goal of personality detection is to map X to a multidimensional label y .

4 Method

In this section, we introduce our EERPD framework, as illustrated in Figure 2. First, we construct a reference library, providing text-label pairs to serve as examples for the personality detection model (§ 4.1). Then, we utilize psychological knowledge to categorize each sentence in text into Emotion Sentences (ES) and Emotion Regulation Sentences (ERS) (§ 4.2). After that, we retrieve the examples through the combination of ES and ERS (§ 4.3). In inference phase, we utilize examples from reference library for personality detection (§ 4.4). And the whole method is shown as Algorithm 1.

4.1 Reference Library Construction

As the model used for personality detection lacks specialized knowledge in psychology, we employ the Retrieval-Augmented Generation (RAG) method to retrieve and inject relevant examples from the reference library. We first constructed a reference library, represented as $C = \{(CX_i, y_i)\}_{i=1}^N$, where CX_i and y_i represents the reference input text and personality label of the i -th instance, and N is the size of the reference library. In our method, we use the training set of the corresponding task as the reference library.

4.2 Sentence Categorization

When performing personality detection, emotion reflects short-term reactions, while emotion regulation represents long-term management of emotional responses. To effectively capture this distinction, we treat them separately in the classification process. For the input text X , we design prompts that clearly define the classification criteria and feed them along with X into the model. The LLM is thus explicitly instructed to classify each sentence x based on its alignment with the defined rules, ensuring that every sentence is forcefully categorized into one of two types: Emotion Sentences ($X_e = \{x_{e1}, x_{e2}, \dots, x_{en}\}$) and Emotion Regulation Sentences ($X_r = \{x_{r1}, x_{r2}, \dots, x_{rn}\}$). Referring to concepts from psychology (Gross, 2008), the classification criteria are defined as follows:

Algorithm 1: EERPD Method

Input: Hyperparameter: α , LLM: $LLM(\cdot)$, Author's text: X , Reference Library: D , EER split Prompt: I_p, I_m , Prediction Prompt: PMT

Output: The inferred personality trait: y

$X_{e,r} \leftarrow LLM(X, I_{e,r});$
 $V_{x_e, x_r} \leftarrow vectorize(X_{e,r});$
 $V_x \leftarrow V_{x_e} + V_{x_r};$
 $Sim \leftarrow [null];$

for each text d in D do

$d_e, d_r \leftarrow LLM(d, I_e, I_r);$
 $V_{d_e, d_r} \leftarrow vectorize(d_e, d_r);$
 $V_d \leftarrow \alpha V_{d_e} + (1 - \alpha)V_{d_r};$
 $sim \leftarrow 1 - \cos(V_x, V_d);$
append sim to Sim ;

$\{t_{1,2}\} \leftarrow argsort_{t \in D} Sim[-2 :];$
 $Egs \leftarrow \{text_{t_1, t_2}, CoT_{t_1, t_2}\};$
 $y \leftarrow LLM(PMT, Egs, X);$

return y ;

Emotion Sentences: The feelings in the sentence are dominated by emotion, it should be an obvious reaction to a recent event and not indicative of a deeper, long-standing trait or belief.

Emotion Regulation Sentences: The feelings in the sentence are dominated by emotion regulation, it should reflect the author's enduring traits rather than immediate circumstances.

For details of the prompt used to accomplish sentence categorization, please refer to Appendix B

4.3 Example Retrieval

People with similar personalities tend to exhibit similar patterns in both emotion and emotion regulation. Therefore, when assessing personality, we retrieve relevant examples from the reference library to assist in detection. To fully utilize both emotion and emotion regulation, we combine them to search for similar examples.

Given the Emotion Sentences X_e and Emotion Regulation Sentences X_r of text X , we compute their vector representations V_{x_e} and V_{x_r} using the roberta-large model, and calculate a weighted embedding with a hyperparameter α as: $V_x = \alpha V_{x_e} + (1 - \alpha)V_{x_r}$. The hyperparameter α adjusts the balance between emotion and emotion regulation. Similarly, we define V_d, V_{d_e} , and V_{d_r} for another text d , where the weighted embedding is: $V_d = \alpha V_{d_e} + (1 - \alpha)V_{d_r}$.

Then we use the similarity function $Sim(V_x, V_d) = 1 - \cos(V_x, V_d)$ to identify the two most analogous texts from the Reference

<Personality traits description> OCEAN is a tool used to ... And the five dimensions are: ...

<Task description> You are an AI assistant who specializes at big five personality traits,, and then you need to give me your choice.

<EER Guidance> The definition of Emotion Regulation and Emotion are as follows: ... Please refer to the following examples to learn how to use Emotion Regulation and Emotion in the text for personality classification.

<EERPD examples> Here are two examples:
Example 1 :{text} + {result} + {reasoning process}
Example 2 :{text} + {result} + {reasoning process}

<Author's Text> The texts from this author are: {Post}

<CoT prompt> Now according to the texts above, the author is more likely to be: y: "Extraversion" or n: "Introversion". Please answer me with the format:...

Figure 3: An overview of prompt in our method.

Library. The selected texts, along with their associated CoTs, serve as examples in 2-shot learning for the LLM.

4.4 Personality Prediction

When conducting personality detection, we use psychological knowledge from the MBTI and OCEAN personality dimension models, and generate model prompts using few-shot and CoT learning strategies. In this way, we emphasize emotion and emotion regulation to direct the model's attention to these aspects. The whole prompt is shown in Figure 3, and more details in A.

Psychological Knowledge. In the prompt, each personality dimension from MBTI or OCEAN is introduced with a precise psychological definition. For instance, "Extroversion (E) or Introversion (I): indicates whether a person is more inclined to draw energy from the external world or the internal world."

Few-Shot and CoT Learning Strategies. We retrieve two examples from Reference Library as § 4.3 mentioned, demonstrating how specific personality traits manifest in textual form through emotion and emotion regulation. Also, we leverage LLM to generate CoTs for each example. The two texts along with CoTs are used as 2-shot examples in the prompt. More details about auxiliary CoT

generation is shown in Appendix C.

5 Experiments

5.1 Datasets

We conduct an evaluation of EERPD using two publicly available datasets: the Kaggle dataset ² and the Essays dataset (Pennebaker and King, 1999).

The Kaggle dataset is sourced from PersonalityCafe ³, and is an extensive collection of textual data aimed at exploring and predicting personality types based on the Myers-Briggs Type Indicator (MBTI). The personality classification follows the MBTI framework (Myers-Briggs, 1991), which segments personality into four dimensions: Introversion/Extraversion (I/E), Sensing/Intuition (S/N), Thinking/Feeling (T/F), and Judging/Perceiving (J/P). The dataset consists of 8,674 entries, each entry representing an individual’s text data (each consisting of 45-50 posts) along with their corresponding MBTI type.

The Essays dataset is a comprehensive collection of text data designed for personality recognition tasks, particularly focusing on the Big Five personality traits (Goldberg, 1990). Given specific instructions, volunteers wrote freely to express their thoughts within a limited time. 2,468 texts along with each author’s Big Five personality traits (Agreeableness, Conscientiousness, Extraversion, Neuroticism, and Openness) makes up this dataset.

Due to the limited API resources, we randomly selected 10% samples from each test set to evaluate our EERPD.

5.2 Baselines

In our experiments, we adopt the following previous methods as baselines.

Statistical Learning: These methods aim to enhance sentiment classification accuracy through statistical learning methods. Tighe et al. (2016) uses SVM with LIWC (Pennebaker, 2001) and linguistic cognitive analysis. Cui and Qi (2017) uses SVM with TF-IDF for feature extraction. Park et al. (2015) uses ridge regression to conduct regression modeling between the language features and users’ Big Five personality traits.

Neural Network Models: These methods leverage neural network architectures to enhance personality detection. W2V+CNN (Rahman et al., 2019) is

a non-pretrained CNN model (Chen, 2015) combined with the word2vec algorithm for context representation. AttRCNN (Xue et al., 2018b) uses a hierarchical structure with a variant of Inception (Szegedy et al., 2017) to encode each post. DDGCN (Yang et al., 2022) employs a domain-adapted BERT to encode each post and a dynamic deep graph network to aggregate posts non-sequentially. Small language models like BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) are fine-tuned on "bert-base-cased" and "roberta-base" backbones, encoding the context for Essays and combining post representations using mean pooling for Kaggles.

Large Language Models: These methods either use LLMs directly or incorporate them as a significant component of the model architecture. Kojima et al. (2022) inserts a reasoning step with "Let’s think step by step", and is adopted as the Zero-shot-CoT baseline in this work. TAE (Hu et al., 2024) improves small model performance in personality detection using text augmentations from LLMs and contrastive learning. PsyCoT (Yang et al., 2023) uses psychological questionnaires as a CoT process, leveraging LLM to perform multi-turn dialogue ratings. We also build a Two-shot CoT prompt as a reference baseline for our EERPD, consisting of two full-text RAG retrieved examples.

5.3 Implementation Details

Due to baseline research and economic considerations, we request the GPT-3.5 API (gpt-3.5-turbo-16k-0613) to obtain results, which is currently the most popular and forms the foundation of ChatGPT. For Zero-shot-CoT, Two-shot-CoT and our EERPD methods, we set the temperature to 0 to get a reliable rather than innovative output. For the PsyCoT and TAE method, we adopt the results from Yang et al. (2023) and Hu et al. (2024). For the AttRCNN and W2V+CNN, we adopt the results from Hu et al. (2024), setting the learning rate for the pre-trained post encoder to 1e-5, and for other parameters 1e-3. For the other fine-tuning based methods, we adopt the baseline results directly from Yang et al. (2023), where the learning rate was set to 2e-5 and the test performance was evaluated by averaging the results of five runs. The evaluation metrics employed in our study include Accuracy and Macro-F1 score.

²<https://www.kaggle.com/datasnaek/mbti-type>

³<http://personalitycafe.com/forum>

| Methods | I/E | | S/N | | T/F | | J/P | | Average | |
|---------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| | Acc. | F1 | Acc. | F1 | Acc. | F1 | Acc. | F1 | Acc. | F1 |
| TF-IDF+SVM | 71.00 | 44.94 | 79.50 | 46.38 | 75.00 | 74.25 | 61.50 | 58.59 | 71.75 | 56.04 |
| Regression | 61.34 | 64.00 | 47.10 | 54.50 | 76.34 | 76.50 | 65.58 | 66.00 | 62.59 | 65.25 |
| AttRCNN | - | 59.74 | - | 64.08 | - | 78.77 | - | 66.44 | - | 67.25 |
| TrigNet | 77.80 | 66.64 | 85.00 | 56.45 | 78.70 | 78.32 | 73.30 | 71.74 | 78.70 | 68.29 |
| DDGCN | 78.10 | 70.26 | 84.40 | 60.66 | 79.30 | 78.91 | 73.30 | 71.73 | 78.78 | 70.39 |
| BERT | 77.30 | 62.50 | 84.90 | 54.04 | 78.30 | 77.93 | 69.50 | 68.80 | 77.50 | 65.82 |
| RoBERTa | 77.10 | 61.89 | 86.50 | 57.59 | 79.60 | 78.69 | 70.60 | 70.07 | 78.45 | 67.06 |
| Zero-shot-CoT | 76.50 | 64.27 | 83.50 | 55.16 | 72.50 | 71.99 | 57.50 | 53.14 | 72.50 | 61.14 |
| Two-shot-CoT | <u>85.93</u> | <u>85.41</u> | 78.89 | <u>77.55</u> | <u>87.44</u> | <u>86.77</u> | <u>69.35</u> | <u>70.36</u> | <u>80.40</u> | <u>80.02</u> |
| TAE | - | 70.90 | - | 66.21 | - | 81.17 | - | 70.20 | - | 72.07 |
| PsyCoT | 79.00 | 66.56 | <u>85.00</u> | 61.70 | 75.00 | 74.80 | 57.00 | 57.83 | 74.00 | 65.22 |
| EERPD(our) | 87.10 | 86.63 | 91.01 | 90.59 | 89.17 | 89.15 | 81.34 | 82.12 | 87.15 | 87.12 |

Table 1: Overall results of EERPD and baselines on the Kaggle dataset.

| Methods | AGR | | CON | | EXT | | NEU | | OPN | | Average | |
|---------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| | Acc. | F1 | Acc. | F1 | Acc. | F1 | Acc. | F1 | Acc. | F1 | Acc. | F1 |
| LIWC+SVM | 51.78 | 47.50 | 51.99 | 52.00 | 51.22 | 49.20 | 51.09 | 50.90 | 54.05 | 52.40 | 52.03 | 50.40 |
| Regression | 50.96 | 51.01 | 54.65 | 54.66 | 55.06 | 55.06 | 57.08 | <u>57.09</u> | 59.51 | 59.51 | 55.45 | 55.47 |
| W2V+CNN | - | 46.16 | - | 52.11 | - | 39.40 | - | 58.14 | - | 59.80 | - | 51.12 |
| BERT | 56.84 | 54.72 | 57.57 | 56.41 | 58.54 | 58.42 | 56.60 | 56.36 | 60.00 | 59.76 | 57.91 | 57.13 |
| RoBERTa | 59.03 | 57.62 | 57.81 | 56.72 | 57.98 | 57.20 | <u>56.93</u> | 56.80 | 60.16 | <u>59.88</u> | 58.38 | 57.64 |
| Zero-shot-CoT | 58.94 | 58.09 | 55.14 | 42.49 | 57.55 | 55.63 | 57.49 | 54.63 | 58.78 | 54.40 | 57.58 | 53.05 |
| Two-shot-CoT | 55.06 | 57.27 | 59.51 | <u>59.63</u> | 52.63 | 52.84 | 53.85 | 53.64 | 57.09 | 57.74 | 55.63 | 56.22 |
| PsyCoT | <u>61.13</u> | <u>61.13</u> | <u>59.92</u> | 57.41 | <u>59.76</u> | <u>59.74</u> | 56.68 | 56.58 | <u>60.73</u> | 57.30 | <u>59.64</u> | <u>58.43</u> |
| EERPD(our) | 64.98 | 65.01 | 68.00 | 68.64 | 62.01 | 63.02 | 56.00 | 56.00 | 61.02 | 60.93 | 62.40 | 62.72 |

Table 2: Overall results of EERPD and baselines on the Essays dataset. We use Accuracy(%) and Macro-F1(%) as metrics. Best results are listed in bold and the second best results are shown with underline.

5.4 Overall Results

The overall results of EERPD and several baselines on Kaggle are listed in Table 1, and on Essays are listed in Table 2. The small model baselines can be divided into three types: statistical learning models (LIWC+SVM, TF-IDF+SVM, Regression), convolution models (W2V+CNN, AttRCNN, TrigNet, DDGCN), and small language models (BERT and RoBERTa). The baselines involved in large language models are: Zero-shot-CoT, Two-shot-CoT, TAE and PsyCoT.

Several key points emerge from these results:

First, EERPD outperforms the baselines on almost all the personality traits, surpassing the fine-tuned models and other prompt-based methods. Specifically, EERPD enhances standard Two-shot-CoT prompting with an average increase of **6.75/7.10** points in Accuracy and Macro-F1 on Kaggle, **6.77/6.50** in Accuracy and Macro-F1 on Essays.

Second, EERPD performs worse than other

methods on the Neuroticism trait. Further analysis reveals that this discrepancy may be due to the low correlation between language-based assessments and self-report questionnaires for Neuroticism. As shown in Park et al. (2015), Neuroticism has the lowest correlation coefficients with self-report questionnaires, indicating that language models struggle to accurately capture and predict this trait, leading to lower prediction accuracy.

Third, although includes two examples with CoT, Two-shot-CoT baseline does not consistently improve the performance of PsyCoT or even Zero-shot-CoT on Essays. Our investigation shows that the examples in Two-shot-CoT are sometimes unhelpful or even negative for detection in Essays, with high conflicts with the sample to be tested. For instance, if both given examples have high Agreeableness, even if the author criticizes their roommate in the test sample, the reasoning still considers it to be high agreeable.

| Methods | Kaggle | | | | |
|--|--------|-------|-------|-------|---------|
| | I/E | S/N | T/F | P/J | Average |
| Zero-shot-CoT | 76.50 | 83.50 | 72.50 | 57.50 | 72.50 |
| Two-shot-CoT | 85.93 | 78.89 | 87.44 | 69.35 | 80.40 |
| EERPD _{w/o E} ($\alpha=0$) | 87 | 85 | 89 | 76 | 84.25 |
| EERPD _{w/o ER} ($\alpha=1$) | 87.02 | 88.17 | 87.94 | 79.76 | 85.72 |
| EERPD | 87.10 | 91.01 | 89.17 | 81.34 | 87.15 |

Table 3: Results of ablation study on Accuracy on the Kaggle dataset.

5.5 Ablation Study

To verify the importance of each component in our EERPD, we conduct an ablation study on 100 samples randomly selected from each of the Kaggle test dataset and Essays test dataset.

Emotion and Emotion Regulation. We first analyze the contributions of Emotion and Emotion Regulation for example retrieval.

EERPD_{w/o E} : EERPD without E, $\alpha = 1.0$, examples are retrieved only based on Emotion Regulation Vectors.

EERPD_{w/o ER} : EERPD without ER, $\alpha = 0.0$, examples are retrieved only based on Emotion Vectors.

Zero-shot-CoT : replace EERPD with simple prompt and no examples.

Two-shot-CoT : replace EERPD with simple prompt, and 2 simple examples using whole text for RAG.

As shown in Table 3, we use three groups for comparison: our overall method shows significant improvements compared to the 2-shot baselines, which means **EERPD is more efficient than the whole article for simple retrieval**. And compared to baselines utilizing only Emotion Regulation (*EERPD_{w/o E}*) or only Emotion (*EERPD_{w/o ER}*), the result can demonstrate that **both components contribute to improvements**.

Parameter α . We investigate the trade-off parameter α in our EERPD, demonstrating the model’s sensitivity to α variations and identifying its optimal range. The results, shown in Figure 4, illustrate performance variations with α on the Kaggle and Essays test datasets.

For the two dataset, both accuracy and Macro-F1 score peaked at $\alpha = 0.7$, then declined. These findings suggest that $\alpha = 0.7$ has the best balance between Emotion Regulation and Emotion, with emotion regulation proving more predictive of personality. Performance drops when α is 0 or 1,

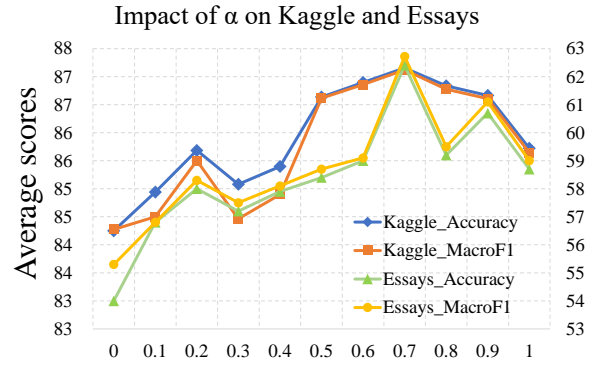


Figure 4: Impact of Alpha on Kaggle and Essays.

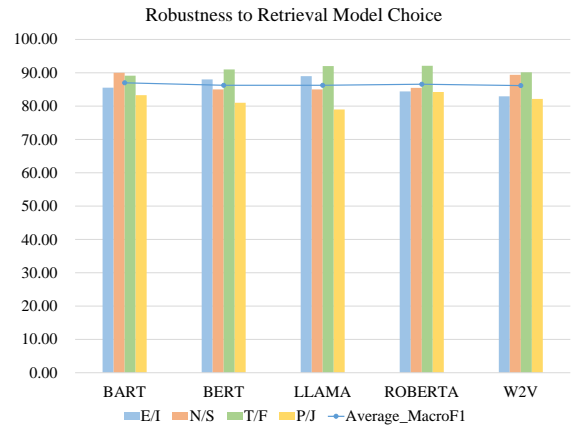


Figure 5: The Performance of Different Retrieval Models on Kaggle dataset.

highlighting that combining both features is more effective than using a single one.

Auxiliary CoT. We evaluate the effect of the auxiliary CoTs generation statistically, using the 100 random samples from Kaggle dataset. And the F1 scores are shown in Table 4. Each data point is the mean of 5 trials. T-test analysis demonstrates that the auxiliary CoTs has statistical significance with p less than 0.05.

| Dataset | E/I | N/S | T/F | P/J |
|----------|-------|-------|-------|-------|
| EERPD | 90.56 | 91.97 | 92.43 | 81.51 |
| w/o CoTs | 78.61 | 83.17 | 86.88 | 79.03 |

Table 4: Results of the ablation study on auxiliary CoTs. EERPD with CoTs outperforms w/o baseline statistically.

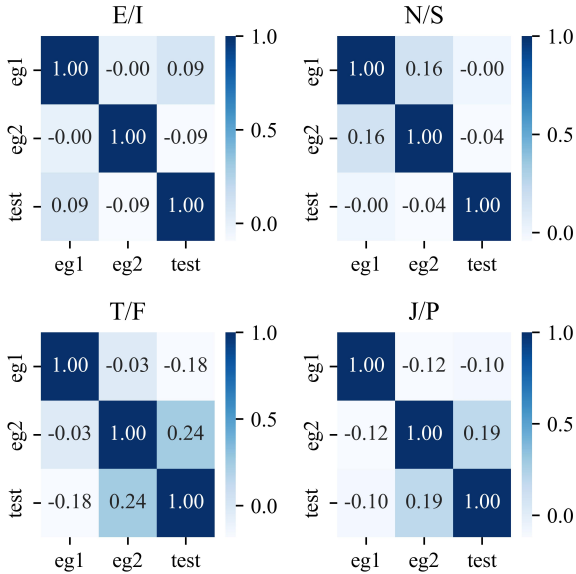


Figure 6: Correlation Analysis on Example Selection.

6 Analysis

6.1 Different Base Model

To evaluate the robustness of our EERPD method across different model architectures, we conducted experiments using various popular language models, including BART (Lewis et al., 2019), BERT (Devlin et al., 2018), LLAMA (Touvron et al., 2023), RoBERTa (Liu et al., 2019), and W2V (Le and Mikolov, 2014). The evaluation dataset consists of 100 samples selected from the Kaggle test dataset.

The results presented in Figure 5, indicate that EERPD maintains consistent performance across different model architectures. This flexibility allows for broader applicability in various settings.

6.2 Correlation Analysis on Example Selection

To evaluate our example selection, we conducted a correlation test between the selected examples and the test set examples. As shown in Figure 6, the result reveals no significant correlation, confirming that our selection method does not leak test set answers to the model. Instead, it identifies examples with similar reasoning patterns. This demonstrates that our method effectively teaches the model relevant reasoning techniques, ensuring that it learns to generalize rather than memorize specific answers. Thus, our approach enhances the model’s ability to perform accurate label predictions based on learned reasoning strategies.

| Dataset | E/I | N/S | T/F | P/J |
|---------|-------|-------|-------|-------|
| Order | 84.16 | 86.03 | 91.14 | 80.74 |
| Random | 85.54 | 89.40 | 89.02 | 79.61 |

Table 5: Results of the study on post orders. The performance of our EERPD is not significantly affected.

| Dataset | E/I | N/S | T/F | P/J |
|----------|-------|-------|-------|-------|
| Standard | 84.23 | 85.26 | 87.33 | 79.27 |
| EERPD | 90.56 | 91.97 | 92.43 | 81.51 |

Table 6: Results of the study on post orders. The performance of our EERPD significantly outperforms standard Two-Shot-CoT baseline.

6.3 Impact of Post Order

The Kaggle dataset includes a collection of posts for each user. These posts are combined in sequence to form a lengthy document, and each post is an input X waiting for detection. However, as Yang et al. (2023) mentioned, researches by Yang et al. (2021, 2022) have shown that sequential encoding of posts is sensitive to order in fine-tuned models. To determine if EERPD are affected by post order, we randomly shuffled the posts and re-evaluated our method using 100 samples. And the F1 results are printed in Table 5. Each score is the average result after five rounds of experiments. The T-test analysis indicates that there is no statistically significant difference between the sequential test and the random-shuffled test.

6.4 Statistical Tests

To statistically evaluate the significance of our approach, we compared the standard Two-shot-CoT baseline with EERPD using the 100 random samples from Kaggle dataset, and the F1 scores are shown in Table 6. Each data point is the mean of 5 trials. T-test analysis demonstrates that our enhancements has statistical significance, with p-values of less than 0.05 for each dimension.

7 Conclusion

In this paper, we introduced EERPD, a novel personality detection method grounded in psychological theories. By leveraging emotion regulation and emotion to retrieve few-shot sample, EERPD provide a new understanding for LLMs to learn and apply psychological knowledges. Experiments on two benchmark datasets demonstrate that EERPD significantly outperforms traditional methods and

other novel prompts, showcasing the importance of integrating emotion regulation as a long-term predictor of personality. This approach uniquely integrates psychological insights to enhance the reasoning abilities of LLMs, offering a new perspective for personality detection.

Limitations

Due to the resource constraints, we only conduct experiments and analysis about LLMs on GPT-3.5. The extent to which GPT-4 or GPT-4o models can benefit from our EERPD remains unknown.

This study primarily focuses on improving the LLM's performance by leveraging the psychological knowledge of Emotion Regulation. How to exploit trainable and tunable models like BERT and LLAMA to further optimize EERPD is left for future investigation.

This method carries certain potential risks. Even with well-intentioned use, personality detection may lead to misjudgments, negatively impacting individuals' careers or social relationships.

Ethics Statement

This work adheres to the ACL Ethics Policy. We assert that, to the best of our knowledge, our work does not present any ethical issues. We have conducted a thorough review of potential ethical implications in our research and found none.

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A Appendix: Prompts for Prediction

To better understand our method, we provide all the prompts in appendix, and record for the whole prediction is in Figure 7.

B Appendix: Sentence Categorization and Prompts

To better understand our method, we provide all the prompts in appendix, and record for EER Sentence Split prompt is in Figure 8.

In our approach, we employ a pre-trained large language model (LLM) to classify sentences into two categories: Emotion (E) and Emotion Regulation (ER). The classification process is guided by a carefully designed prompt, which instructs the model to evaluate each sentence and assign it to one of the two categories based on its semantic content. Sentences that express transient emotional states or reactions to immediate events are classified as Emotion sentences (E), while those that reflect long-term emotion management, control, or behavioral patterns are categorized as Emotion Regulation sentences (ER). Importantly, the model is forced to classify all sentences, including those that may appear neutral, by relying on contextual clues or implicit emotional tones.

While a three-class framework might allow for the explicit categorization of neutral sentences, it introduces additional complexity and risks increasing ambiguity, as many sentences could fall into a gray area between categories. In contrast, the binary classification we employ reduces this potential overlap and ambiguity, ensuring that each sentence is consistently classified. This approach enhances interpretability and streamlines the model's decision-making process, avoiding the challenge of sentences being ambiguously labeled as neutral when they might carry subtle emotional or regulatory signals. By focusing on binary classification, the model maintains a clear decision boundary, ensuring that all sentences contribute meaningfully to the overall personality prediction.

For the scientific validity of our classification criteria, we conducted the following experiments:

1. Automated Label Consistency Experiment

We first conducted two rounds of automated labeling on small samples from two datasets to assess the model's consistency in performing classification tasks. Specifically, we employed a large language model (LLM) to classify sentences in these samples based on predefined criteria for Emotion (E) and Emotion Regulation (ER). After two rounds of automated classification, we calculated the label consistency between each round. The results showed that the agreement across the two datasets exceeded 95%, indicating that the model consistently adhered to the fixed classification criteria. This result reinforces our confidence in the scientific validity of the classification criteria and the model's capability to handle this task reliably.

2. Comparison with Human Labeling Standards In the second experiment, we compared the model's classification results with human labeling standards. To ensure the reliability of the human annotations, we randomly selected 100 manually labeled sentences. We then compared the model's classifications to the human labels. The results showed an 86% agreement between the model and human annotations. While there was some discrepancy compared to fully human labels, we consider this result to be strong evidence of the model's labeling accuracy, especially in large-scale applications.

C Appendix: Prompt for Generation of auxiliary CoT

To better understand our method, we provide all the prompts in appendix, and record for generating the CoT in Reference Library is in Figure 9.

Record of prediction prompt

MBTI is a tool used to assess a person's psychological preferences and personality types, and there are 16 different types of MBTI, each consisting of four letters representing four dimensions of preference. And the four dimensions are:

Extroversion (E) or introversion (I) : indicates whether a person is more inclined to draw energy from the outside world or the inside world.

Sense (S) or intuition (N) : indicates whether a person is more inclined to focus on concrete facts and details, or abstract concepts and possibilities.

Thinking (T) or emotion (F) : indicates whether a person is more inclined to make decisions using logic and principles, or values and emotions.

Judgment (J) or perception (P) : indicates whether a person is more inclined to a planned and organized lifestyle, or a flexible and random lifestyle.

You are an AI assistant who specializes at MBTI personality traits. I will give you texts from the same author, and then I will ask you the author's MBTI type, and then you need to give me your choice.

The definition of Emotion Regulation and Emotion are as follows:

1. Emotion Sentences: These sentences should be clearly linked to immediate, temporary feelings that arise from specific, recent incidents or current situations. The key is that the emotion should be an obvious reaction to a recent event and not indicative of a deeper, long-standing trait or belief.

2. Emotion Regulation Sentence: These sentences must consistently reflect the speaker's enduring traits. They should not be influenced by immediate circumstances but rather indicate a persistent and characteristic ability of controlling emotion.

Please refer to the following examples to learn how to use Emotion Regulation and Emotion in the text for personality classification.

I will give you 45~50 posts from the same user, divided by |||. Please use MBTI personality analysis to help me analyze what the user's MBTI is most likely to be.

Here are two examples:

Example 1:

The posts of this user are: +cot. iloc [e1][' posts ']+

Result: """+cot. iloc [e1][' type ']+""

Process: """+cot. iloc [e1][' cot ']+""

Example 2

The posts of this user are: """+cot. iloc [e2][' posts ']+""

Result: """+cot. iloc [e2][' type ']+""

Process: """+cot. iloc [e2][' cot ']+""

Now, analysis the user's MBTI type with your reasoning process.

The user's post reads as follows:

"""+post+""

Your response should follow the following format:

Result: {The four letters represent the type of mbti you guessed}

Process: {your reasoning process}.

Figure 7: A complete record of prediction

Record of EER Sentence Split

I am a sentence sentiment adjudicator specialized in distinguishing the sources of emotions in sentences – whether they stem from the speaker's current mood or their inherent personality. Your task is to assist me by examining the text and discerning the dominant influence in each sentence, based on these highly refined definitions :

1. Emotion Sentences: These sentences should be clearly linked to immediate, temporary feelings that arise from specific, recent incidents or current situations. The key is that the emotion should be an obvious reaction to a recent event and not indicative of a deeper, long-standing trait or belief.
 - Highly Refined Definition : Look for signs that the emotion is an immediate response to a particular event, is temporary, and doesn't reflect an ongoing pattern of thoughts or behaviors.
 - Examples and Analysis:
 - "Sex can be boring if it's in the same position often. For example me and my girlfriend are currently in an environment where we have to creatively use cowgirl and missionary. There isn't enough..." – Emotion, as it describes a current, specific situation causing temporary boredom.
 - "I'm thrilled about the concert tonight!" – Emotion, as the excitement is tied to a specific, imminent event (the concert).
 - "I am anxious because of the upcoming exam." – Emotion, since the anxiety is a temporary response to a specific future event (the exam).
 - "I am angry with my friend for something they did last week." – Emotion, because the anger is a reaction to a specific, recent event (the friend's action last week).
2. Emotion Regulation Sentence: These sentences must consistently reflect the speaker's enduring traits. They should not be influenced by immediate circumstances but rather indicate a persistent and characteristic ability of controlling emotion.
 - Highly Refined Definition : Determine if the expression is reflective of a longstanding personality trait for emotion control, consistent over time and not a reaction to a specific, recent circumstance.
 - Examples and Analysis:
 - "I'm finding the lack of me in these posts very alarming." – Emotion Regulation, as it reflects a long-term concern about self-representation rather than an immediate emotional reaction.
 - "Giving new meaning to 'Game' theory." – Emotion Regulation, as it expresses a general viewpoint on a concept, not about temporary feelings.
 - "Hello *ENTP Grin* That's all it takes. Than we converse and they do most of the flirting while I acknowledge their presence and return their words with smooth wordplay and more cheeky grins." – Emotion Regulation, as it describes a consistent behavior pattern rather than a reaction to a specific event.
 - "Real IQ test I score 127. Internet IQ tests are funny. I score 140s or higher. Now, like the former responses of this thread I will mention that I don't believe in the IQ test. Before you banish ..." – Emotion Regulation, as it reflects a long-standing skepticism towards IQ tests, not an immediate emotional reaction.

Special Case: Any sentences containing only a URL should be classified as 'Emotion Regulation'.

- "<http://www.youtube.com/watch?v=4V2uYORhQOk>" – Emotion Regulation, because it is a pure URL.
- "<http://playeressence.com/wp-content/uploads/2013/08/RED-red-the-pokemon-master-32560474-450-338.jpg>" – Emotion Regulation, as it is a URL.

Ambiguous Examples and Detailed Analysis:

1. "The last thing my INFJ friend posted on his facebook before committing suicide the next day. Rest in peace~" – Emotion. Although it mentions an INFJ personality type, the focus is on the immediate emotional reaction to the friend's recent suicide.
2. "I often find myself reflecting deeply on my experiences." – Emotion Regulation. This indicates a consistent trait of introspection, not linked to a specific, recent event.

For each sentence provided, carefully determine whether it primarily reflects 'Emoiton' or 'Emotion Regulation', based on these highly refined criteria. List each sentence and categorize it as either 'Emotion' or 'Emotion Regulation'.

The texts from this author are: "" + post + "".

Respond in the following format without any reason or explain :

0. [Emotion/Emotion Regulation]
1. [Emotion/Emotion Regulation]
2. [Emotion/Emotion Regulation]

Focus meticulously on these criteria to maximize the accuracy and consistency of classification.

Figure 8: A complete record that EERPD is applied to split the text into E or ER part.

Record of CoT Generation

Suppose you are a psychologist with a keen interest in personality types and online behavior. You know that MBTI is a tool used to assess a person's psychological preferences and personality types, and there are 16 different types of MBTI, each consisting of four letters representing four dimensions of preference. And the four dimensions are:

- Extroversion (E) or introversion (I) : indicates whether a person is more inclined to draw energy from the outside world or the inside world.
- Sense (S) or intuition (N) : indicates whether a person is more inclined to focus on concrete facts and details, or abstract concepts and possibilities .
- Thinking (T) or emotion (F) : indicates whether a person is more inclined to make decisions using logic and principles, or values and emotions.
- Judgment (J) or perception (P) : indicates whether a person is more inclined to a planned and organized lifestyle, or a flexible and random lifestyle .

I will give you 45~50 posts from the same user, divided by |||. Please use MBTI personality analysis to help me analyze what the user's MBTI is most likely to be. I will give you 45~50 posts from the same user, divided by |||, and the MBTI type of the user. Please use MBTI personality analysis to help me analyze why the user is this MBTI type.

Here is an example:

Example:

The posts of this user are: 'Wow, thank you for this thread! Physical vs. metaphysical is a great topic! I find that I am very much the same way your are. How can I put it I have my days. :) The more I develop my xSxJ, the ...||| my room. I like to be in my bad, next to my books, with my fan on and laptop nearby .||| I wouldn't say that I can read souls – but I can see potential . I can sense sadness, happiness, uneasiness, etc. I can tell when someone is not happy where they are and with what they are doing with ...||| thank you for being so polite ! :) ||| I find eye contact is key. I acknowledge their existence and importance by maintaining eye contact with them throughout the conversation . Not by staring in their eyes in a creeper way, but by making ...||| As an INFJ male I can somewhat relate to your post. A very close lady friend of mine and I were like this for years! I had always liked her and could read her fairly well. I knew when she needed ...'

Result: INFJ

Process: Based on the posts you provided, I would guess that the user is an INFJ personality type. INFJs are known as the advocates, who are quiet and mystical, yet very inspiring and tireless idealists. They are often deeply spiritual, compassionate, and intuitive. They value harmony, authenticity, and personal growth. They can also be very sensitive, private, and perfectionistic.

Some clues that suggest the user is an INFJ are:

First of all, I think the user is an introvert (I). The user prefers to spend time alone in his room with books and laptop, rather than socializing with many people. He also seem to be more focused on his inner world of thoughts and feelings, rather than the outer world of events and actions.

Secondly, I think the user is an intuitive (N). He is interested in abstract concepts and possibilities, such as physical vs. metaphysical. He can see the potential in people and situations, and he is not limited by the facts and details. He also has a wide range of knowledge and interests, and he is constantly learning and innovating.

Thirdly, I think the user is a feeler (F). He makes decisions based on his values and emotions, rather than logic and principles. He can sense the emotions of others and empathize with them. He is polite and respectful, and he values harmony and cooperation.

Lastly, I think the user is a judger (J). He prefers a planned and organized lifestyle, rather than a flexible and random one. He has a clear sense of direction and purpose, and he likes to achieve his goals. He also have a strong xSxJ side, which means he can use his sensing function to deal with reality and details when necessary.

Therefore, based on my analysis, I think the user's MBTI type is INFJ. INFJs are known as the advocates or the counselors. They are idealistic, creative, compassionate, and insightful. They have a vision of how to make the world a better place, and they use their intuition and feeling to inspire and motivate others. They are also loyal, dedicated, and supportive of their friends and loved ones.

Now, you should generate the {Process}, according to the MBTI type and the posts given to you.

The user's MBTI type is: ""+type+""", and the user's posts are: ""+post+""".

Your response should follow the following format:

Process: {your reasoning process}.

""""

Figure 9: A complete record for the Generation of auxiliary CoT in Reference Library.