

RecEarlyMind @ eRisk 2026: Conversational Depression Detection Using Transformer-Based Language Models

Notebook for the eRisk Lab at CLEF 2026

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Abstract

Depression is one of the most significant mental health challenges worldwide, making early detection an important research problem in natural language processing and artificial intelligence. This paper describes the participation of Team RecEarlyMind in CLEF 2026 eRisk Task 1 on Conversational Depression Detection. The task focuses on identifying signs of depression from conversational interactions generated through Large Language Model (LLM) personas. Our approach utilizes the Meta-Llama-3-8B-Instruct model together with conversational text analysis techniques to classify conversations into depression-related and non-depression-related categories. The proposed system includes preprocessing, contextual understanding, and prompt-based analysis for effective prediction. Experimental results demonstrate the effectiveness of our approach in detecting depressive symptoms from conversational data. This work highlights the potential of LLM-based systems for supporting early mental health risk assessment and conversational depression detection.

Keywords

Conversational Depression Detection, Large Language Models, Meta-Llama-3-8B-Instruct Model, eRisk 2026

enables effective modeling of long-range contextual dependencies and nuanced linguistic patterns within conversations, making them well-suited for conversational depression detection. In addition, prompt engineering and contextual reasoning techniques further improve the capability of these models to extract psychologically relevant information from dialogue, supporting more reliable identification of depression-related symptoms.

Several studies have explored the use of NLP and deep learning techniques for mental health assessment from textual data, including approaches for depression detection [4]. Trotzek et al. investigated recurrent neural network architectures for depression detection from social media posts [6] and demonstrated the effectiveness of deep contextual representations for identifying depressive behavior. These studies emphasize the growing importance of AI-driven approaches in supporting early psychological risk assessment.

Research in conversational AI and mental health analysis also highlights the importance of contextual understanding, emotional reasoning, and ethical AI deployment. Turcan et. al., introduced benchmark datasets for mental health analysis and demonstrated how conversational context can improve depression detection performance [4]. Likewise, Zogan et. al., explored transformer-based architectures for mental health prediction and reported that contextual attention mechanisms improve the identification of depression-related linguistic patterns. These approaches indicate that transformer-driven conversational systems can effectively support automated mental health assessment tasks.

In this work, we present a conversational depression detection framework [7] based on transformer-driven contextual analysis techniques [5] and prompt-based conversational understanding. The proposed system includes conversational preprocessing, contextual feature extraction, emotional pattern analysis, and depression classification using Large Language Models [8]. The experiments were performed using the datasets and evaluation protocols provided in the CLEF 2026 eRisk Task 1 challenge. The obtained results demonstrate the effectiveness of transformer-based conversational analysis techniques for detecting depressive symptoms from dialogue interactions and highlight the potential of AI-assisted systems in supporting early mental health risk detection and conversational healthcare applications.

2. Experimental Setup

The experiments were conducted using transformer-based Large Language Models for conversational depression detection [4] in CLEF 2026 eRisk Task 1. The convers

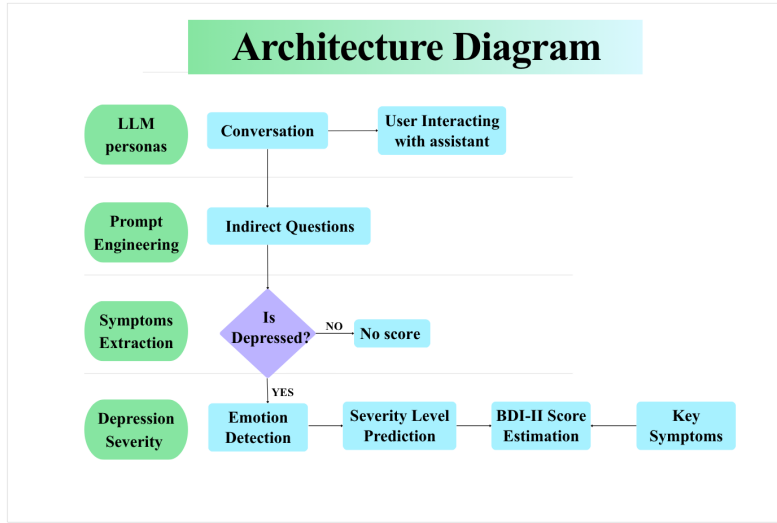


Figure 1: System Architecture for eRisk and Depression Detection

as context for every interaction, allowing the model to capture semantic relationships, emotional expressions, and contextual dependencies across dialogue turns.

The submitted system did not implement an early stopping strategy. Conversations continued until the organizer-defined interaction process was completed, after which the final conversation history was used for prediction. Based on the complete dialogue history, the Meta-Llama-3-8B-Instruct model generated the depression prediction, estimated the BDI-II score, and ranked the depression symptoms according to the official task prompt and required output format.

4. Results and Analysis

The performance of the proposed conversational depression detection [1] system was evaluated using the official evaluation framework provided in CLEF 2026 eRisk Task 1. The task focused on identifying depressive symptoms from conversational interactions with LLM personas while encouraging early decision making [11]. The evaluation considered multiple metrics including Depression Case Hit Rate (DCHR) [9] (DCHR), Average Depression Ordinal Distance Loss (ADODL), Average Symptoms Hit Rate (ASHR), Latency-weighted Depression Case Hit Rate (LDCHR), and Latency-weighted Average Symptoms Hit Rate (LASHR). These metrics measure not only the correctness of predictions but also the efficiency of conversational interactions before generating predictions.

4.1. Results for eRisk: Conversational Depression Detection

Our team, **RecEarlyMind**, participated with one official run in the shared task evaluation. The obtained results are presented in Table 1. The proposed approach achieved a DCHR score of 0.3000, an ADODL score of 0.8071, an ASHR score of 0.1625, an LDCHR score of 0.2013, and a LASHR score of 0.0977. The results demonstrate the capability of the proposed Meta-Llama-3-8B-Instruct-based conversational analysis framework in identifying depressive

Table 3
Example Outputs of the Proposed System

Conversation Snippet	Predicted Class	Detected Indicators
"I feel tired all the time and I do not enjoy things anymore."	Depression	Hopelessness, Loss of Interest
"I have been avoiding my friends recently and prefer staying alone."	Depression	Social Withdrawal, Isolation
"I am doing well and spending time with my family and friends."	Non-Depression	Positive Emotional State
"Sometimes I feel worthless and cannot focus on my daily activities."	Depression	Negative Self-Perception, Low Motivation
"I completed my work today and felt productive."	Non-Depression	Positive Behaviour

The generated outputs demonstrate that the proposed system can identify contextual emotional patterns and conversational cues associated with depressive behaviour. The proposed Meta-Llama-3-8B-Instruct framework effectively distinguishes depression-related and non-depression-related interactions using contextual semantic understanding and conversational reasoning.

Table 4
Example Outputs of Conversational Depression Detection

Conversation Summary	BDI Score	Detected Symptoms
The user expressed tiredness, sleep disturbances, work stress, difficulty relaxing, and constant overthinking during the conversation.	12	Sadness, Indecisiveness, Irritability, Concentration Difficulty
The user reported social withdrawal, lack of motivation, feelings of worthlessness, and difficulty concentrating on daily activities.	18	Social Withdrawal, Low Self-Esteem, Sadness, Sleep Disturbance

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Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT and Grammarly in order to improve grammar, sentence structure, language clarity, and content refinement. The authors also used Generative AI tools for assistance in drafting and organizing portions of the manuscript. After using these tools, the authors carefully reviewed, edited, and validated the content as needed and take full responsibility for the final publication content.

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