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Generative AI for Multilingual Mental Health Detection and Early Support: An Integrated Framework

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Abstract

Early detection of mental health conditions is critical for timely intervention; however, multilingual and low-resource populations remain underserved due to limited annotated data and language-specific tools. This study proposes an integrated dual-framework that leverages Generative AI (GenAI) for multilingual mental health detection and support. The framework combines large language models (LLMs) for early detection of depressive signals in social media data with a multilingual AI-powered assistant that provides initial support to users. To address data scarcity in low-resource languages, GenAI is used to generate culturally relevant, linguistically diverse synthetic training data, thereby improving model robustness and coverage. Experimental results demonstrate that the proposed hybrid multilingual model improves early-stage depression detection, achieving a 20% increase in recall and an 8% improvement in F1-score compared to baseline transformer models. The framework emphasises detection accuracy,

linguistic adaptability, and user-centric interaction, offering a scalable, ethically grounded approach to culturally sensitive, AI-driven mental health support and early intervention.

Keywords: Generative AI, Multilingual Mental Health Detection, Depression Detection, Synthetic Data Augmentation, Multilingual Transformer Models, Reinforcement Learning with Human Feedback (RLHF), AI-Powered Mental Health Assistant

1 Introduction

Mental health disorders, including anxiety and depression, are major contributors to global disability. According to the World Health Organisation, approximately one in eight individuals worldwide is affected by a mental health condition [1]. Despite this prevalence, access to timely, culturally appropriate care remains limited, particularly for underserved and multilingual populations. Barriers such as social stigma, lack of awareness, and language diversity often delay early detection and intervention.

Recent research highlights the potential of social networks as a scalable and non-intrusive source of mental health monitoring, where user-generated content reflects behavioral and linguistic indicators of psychological states [2, 3]. However, existing approaches are limited by limited annotated data, cultural bias, and poor performance in low-resource languages. Generative Artificial Intelligence (GenAI), particularly large language models (LLMs), offers a promising solution by enabling the generation of culturally relevant and linguistically diverse synthetic data, as well as supporting context-aware analysis of emotional and behavioural signals [4, 5]. Despite these advances, the use of GenAI for integrated multilingual mental health detection and support remains underexplored.

This study addresses these challenges by investigating how early-stage depression detection can be improved across multilingual and low-resource settings while enabling accessible, culturally adaptive support. To this end, we propose an integrated dual framework that combines a multilingual depression-detection model with an AI-powered mental health assistant. The framework leverages synthetic data enhancement to address data scarcity and incorporates lexical, syntactic, and behavioral features to improve contextual understanding. Experimental results demonstrate improved detection performance, with gains in recall and F1-score over baseline transformer models.

To address the identified challenges, this study proposes a GenAI-based framework with the following objectives:

1. Develop a multilingual depression detection model for the early identification of depressive signals from social media data.
2. Design a GenAI-powered conversational assistant that provides culturally adaptive and language-sensitive mental health support.
3. Mitigate data scarcity and model bias through synthetic data augmentation for low-resource languages.

4. Integrate lexical, syntactic and temporal features to enhance contextual modelling and improve detection performance.

The main contributions of this work are as follows:

1. We propose a multilingual GenAI-based model for early depression detection from social media data.
2. We develop an AI-powered conversational assistant that delivers culturally adaptive and language-sensitive mental health support.
3. We employ a synthetic data augmentation strategy to address data scarcity and reduce bias in low-resource language settings.
4. We integrate lexical, syntactic, and temporal features to enhance contextual understanding and improve model performance.

The remainder of this paper is organised as follows. Section 2 reviews related work in multilingual natural language processing (NLP) and AI-based mental health. Section 3 presents the proposed hybrid framework, including data collection, model development, and multilingual methodologies. Section 4 describes the experimental setup, and Section 5 reports the experimental results. Section 6 discusses the findings in detail and outlines the implications, limitations, and directions for future research. Finally, Section 7 concludes the paper.

2 Related Works

The application of artificial intelligence (AI) in mental health has driven significant advances over the past decade, particularly through the use of machine learning (ML) and natural language processing (NLP) to detect emotions, predict mood states, and deliver conversational interventions. Early progress in improving the accessibility of cognitive behavioural therapy (CBT) has been facilitated by AI-powered chatbots. Systems such as Woebot and Wysa are capable of conducting structured therapeutic interactions with minimal human involvement [6, 7].

Simultaneously, social media platforms have emerged as valuable resources for the early identification of mental health conditions. Linguistic and behavioural signals embedded in user-generated content have been shown to correlate strongly with conditions such as depression, anxiety, and suicidal ideation [3, 8]. Indicators such as increased use of first-person pronouns, negative sentiment expressions, and temporal changes in language patterns have been identified as reliable markers of psychological distress. These developments enable large-scale, non-intrusive monitoring of mental health without imposing additional burden on individuals.

Despite these advances, most existing models are trained predominantly on English-language data and reflect Western cultural contexts, limiting their effectiveness in multilingual and diverse populations. Multilingual mental health detection remains challenging due to linguistic variability, cultural differences in emotional expression, and the scarcity of annotated datasets for low-resource languages [9, 10]. These limitations hinder the development of inclusive and generalisable AI systems.

Recent progress in large language models (LLMs), such as GPT-3, LLaMA, and PaLM, has introduced new opportunities to address these challenges. Generative AI

(GenAI) has demonstrated the ability to generate linguistically diverse and culturally relevant synthetic data, as well as to support multilingual and context-aware modelling. Studies have shown that GenAI can facilitate the development of multilingual mental health assistants, expand training datasets, and enhance the cultural sensitivity of AI systems [11, 12]. Furthermore, GenAI has been successfully applied in synthesising clinical data, designing culturally aware prompts, and improving the conversational quality of AI-driven healthcare applications, thereby enhancing their practical relevance and effectiveness.

2.1 AI in Mental Health

Artificial intelligence (AI), particularly machine learning (ML) and natural language processing (NLP), has shown strong potential in supporting mental health assessment and intervention. Prior studies demonstrate that linguistic patterns in text and speech can differentiate between clinical and non-clinical emotional states [13]. Building on this, various NLP-based approaches have been developed to detect indicators of psychological distress, including cognitive impairment and emotional instability [7].

AI-powered conversational agents have further improved accessibility to mental health support. Systems such as Woebot and Wysa utilise cognitive behavioural therapy (CBT) principles to deliver structured therapeutic interactions [6, 14]. However, these systems often rely on predefined responses and rigid linguistic frameworks, limiting their adaptability and effectiveness across diverse users and multilingual contexts.

Recent advances in deep learning have introduced more flexible and powerful approaches for modelling mental health signals. Transformer-based architectures have demonstrated strong performance in capturing complex linguistic patterns from personal data sources such as diary entries and daily logs [15]. While these models improve predictive capability, challenges remain in terms of multilingual adaptability, contextual understanding, and data availability—highlighting the need for more robust, inclusive, and generative AI-driven solutions.

2.2 Social Media for Mental Health Monitoring

Social media platforms provide a rich and scalable source of data for analysing psychological well-being. Early studies demonstrated that linguistic patterns on platforms such as Twitter can be used to predict depression [16]. Subsequent research identified key indicators of mental distress, including increased use of first-person pronouns, negative emotional expressions, and temporal references in user-generated content [17].

More recent approaches have applied sentiment analysis, sequence classification, and topic modelling techniques to detect conditions such as anxiety and suicidal ideation [3, 8]. The Computational Linguistics and Clinical Psychology (CLPsych) community has further advanced this field by establishing benchmark datasets and shared tasks for systematic model evaluation [18]. Despite these advances, challenges remain in generalising models across diverse populations and reducing false positives in real-world applications.

To address these limitations, recent studies have explored multimodal approaches that integrate textual content with temporal features (e.g., posting behaviour), user interactions, and visual data [19]. These hybrid models improve the representation of mental health signals; however, their applicability across languages and cultural contexts remains limited.

2.3 Multilingual Challenges in Mental Health AI

A major limitation of current AI-driven mental health systems is their reliance on English-language datasets. The scarcity of annotated corpora in low-resource languages significantly restricts the applicability of detection models for non-English-speaking populations [20]. Furthermore, cultural and linguistic differences strongly influence how individuals express emotions, making direct translation approaches insufficient for accurate mental health assessment.

Prior studies emphasise the need for culturally and linguistically adaptive models to ensure equitable mental health support [9, 21]. Evidence suggests that depressive language patterns vary significantly across languages such as Hindi and Arabic, indicating that models must account for region-specific linguistic characteristics. To bridge this gap, multilingual representations such as XLM-RoBERTa and zero-shot transfer learning have been explored. However, these approaches often struggle with highly dialectal or under-represented languages [22].

These limitations highlight the need for more flexible approaches, particularly those that leverage synthetic data generation to capture linguistic diversity and cultural nuances. Such strategies can improve model adaptability and support the development of inclusive, multilingual mental health detection systems.

2.4 Generative AI in Healthcare

Recent advances in Generative Artificial Intelligence (GenAI), driven by large language models (LLMs) such as Pathways Language Model (PaLM), Generative Pre-trained Transformer (GPT-3), and Large Language Model Meta AI (LLaMA), have significantly transformed content generation and data-driven applications in healthcare. GenAI has been applied to synthesise medical records [23], augment training datasets derived from real patient data [24], and generate synthetic data to address data scarcity [25]. These approaches have been shown to improve model performance, reduce administrative burden, and enhance scalability in healthcare systems.

In the context of mental health, recent studies have explored the use of GenAI to generate synthetic text that reflects psychological states such as depression and anxiety, thereby enriching training data for detection models [11, 26]. Synthetic data generation is particularly valuable for addressing class imbalance and improving representation in low-resource languages and rare clinical scenarios. Furthermore, multilingual LLMs have been investigated for developing conversational agents capable of delivering empathetic and context-aware mental health support. For example, ChatGPT-based systems have demonstrated high levels of linguistic coherence and emotional appropriateness across multiple languages [27].

Table 1 Summary of Methods and Findings in GenAI-Driven Mental Health Research

Research Area	Study	Method Used	Key Findings	Limitations
AI in Mental Health	[6]	Rule-based CBT chatbot	Reduced depressive symptoms in young adults	Limited personalization; English-only
	[14]	ML mood tracking app	Accurate mood prediction; moderate adherence	No real-time automation
	[15]	BERT emotion analysis	High accuracy; captured temporal patterns	Limited linguistic diversity
Social Media for Monitoring	[16]	Lexical + behavioral Twitter analysis	Linguistic cues aligned with depressive states	Focused on postpartum cases; English-only
	[3]	Sentiment + topic modeling	Identified anxiety/depression markers	Poor generalization to diverse cultures
	[8]	DL suicide-risk classification	Achieved state-of-the-art on Reddit	High false positives; cultural nuance missing
Multilingual Challenges	[20]	Cross-lingual NLP (XLM-R) survey	Highlighted gaps in low-resource languages	Weak performance on dialects
	[9]	MH lexicons in Hindi/Arabic	Revealed cultural variation in expression	Need for culturally adaptive models
	[28]	ML on multilingual posts	Good multilingual performance	Insufficient regional/dialect data
Generative AI in Healthcare	[23]	GAN-based synthetic EHR	Improved privacy and robustness	Limited to structured data
	[11]	Conditional GAN text samples	Balanced rare cases; improved accuracy	Quality/realism concerns
	[27]	ChatGPT mental health assistant	High fluency and empathy in multiple languages	Ethical risks; hallucination; no clinical validation

Despite these advances, important concerns remain regarding the ethical use, safety, reliability, and clinical validity of GenAI-based mental health applications. These challenges highlight the need for robust, transparent, and culturally sensitive AI systems in healthcare.

2.5 Research Gaps

Despite substantial progress in AI-based mental health research, several critical gaps remain. As summarised in Table 1, existing studies typically focus on either mental health detection or intervention, with limited integration of both capabilities into a unified framework. In addition, many approaches rely on structured clinical datasets or English-language corpora, reducing their applicability in multilingual, informal, and real-world environments such as social media.

Furthermore, the potential of GenAI to generate culturally and linguistically relevant synthetic data for low-resource languages remains underexplored. Current models often fail to capture the diversity of emotional expression across different cultural and linguistic contexts, limiting their generalisability. There is also a lack of comprehensive systems that combine early-stage mental health detection with real-time, personalised support in users' native languages.

To address these limitations, this study proposes an integrated GenAI-based framework that leverages social media data for early detection of mental depression and employs multilingual LLM-based conversational agents to provide context-aware mental health support. By combining detection and intervention within a unified system, the proposed approach aims to enhance accessibility, inclusivity, and scalability of AI-driven mental health care, particularly for underserved and multilingual populations.

3 Methodology

This section presents the methodology used to develop and evaluate the hybrid multilingual depression detection system illustrated in Fig. 1. The proposed approach is structured around four key components, each corresponding to a primary objective: (1) early detection of depression through linguistic analysis; (2) multilingual inclusion in high and low-resource languages; (3) bias mitigation through synthetic data augmentation; and (4) integration of lexical, syntactic, and temporal features for enhanced contextual modelling and improved performance.

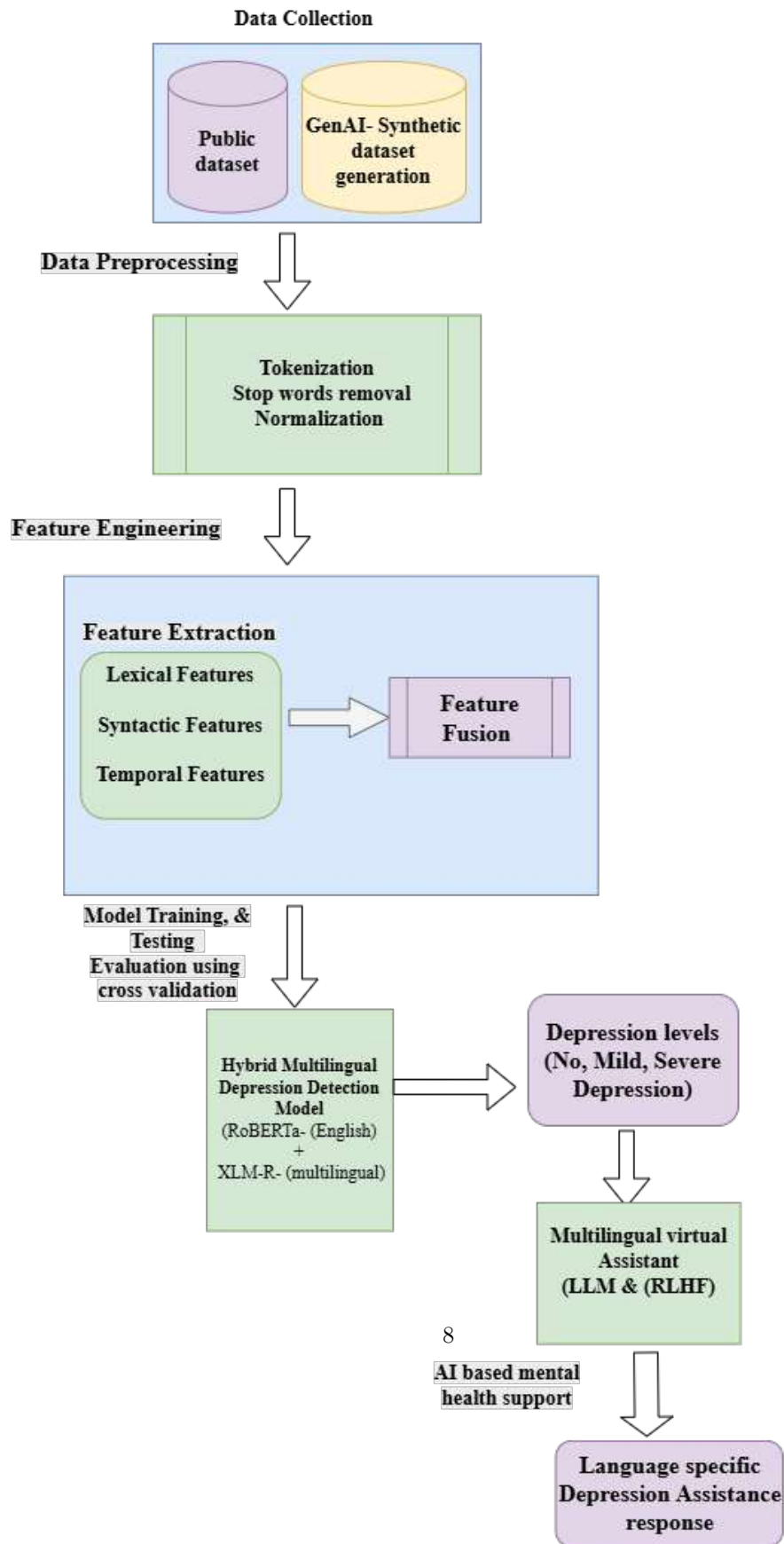


Fig. 1 Hybrid multilingual depression detection architecture integrating transformer-based embeddings (RoBERTa and XLM-R) with lexical, syntactic, and temporal feature fusion for context-aware classification of depression levels, followed by an AI-powered multilingual assistant for adaptive mental health support.

3.1 Dataset Collection and Preprocessing

3.1.1 Public Dataset

The dataset comprises multilingual social media posts annotated across different levels of psychological depression. English-language data were obtained from established mental health corpora, while datasets for Tamil, Hindi, and Arabic were collected using publicly available open-source resources. To address the limited availability of annotated data in low-resource languages, GenAI-based synthetic data generation was employed to enhance dataset diversity and representation.

Prior to model input, all data underwent language identification to ensure accurate processing of multilingual content. Each post was analysed using FastText-LID and langid.py to determine the dominant language at the sentence level. Posts containing multiple languages were identified as code-switched.

To effectively process such content, a hybrid encoding strategy was adopted. English text was encoded using RoBERTa, while non-English content was processed using the multilingual XLM-R model. For code-switched inputs, a mixed-language approach was applied: segments were encoded using their respective models, and the resulting embeddings were combined prior to feature fusion. In cases of token-level language switching, the XLM-R encoder was used to preserve semantic continuity. This approach ensures consistent representation of multilingual and hybrid-language posts without loss of contextual or cultural information.

Data preprocessing included the removal of URLs and stop words, normalisation of slang and emoticons, tokenisation, and lowercasing. Language identification further enabled routing of text to the appropriate transformer backbone, ensuring optimal encoding for both monolingual and multilingual inputs.

3.1.2 GenAI-Based Synthetic Dataset Generation

To address data scarcity and class imbalance in low-resource languages, synthetic social media posts were generated using multiple GenAI models, including GPT-4, Mistral, and LLaMA. These models were prompted to produce linguistically and culturally appropriate content reflecting varying levels of psychological distress, particularly depression.

The data augmentation process involved three key steps:

1. Prompt engineering to generate culturally relevant linguistic patterns, including local idioms and expressions related to emotional states.
2. Back-translation and paraphrasing to increase linguistic diversity and variability.
3. Controlled generation to maintain class balance across emotional categories, such as neutral, anxiety, and depression.

Synthetic data generated was integrated with real-world samples to improve model robustness and reduce linguistic bias.

To ensure quality and reliability, the synthetic data underwent a multi-stage validation process. First, automated language verification was performed to confirm linguistic accuracy. Coherence and fluency were assessed using language model scoring

and perplexity thresholds to eliminate grammatically incorrect or nonsensical samples. Subsequently, a stratified sample (10%) from each language group was manually reviewed by multilingual annotators with expertise in psychology and linguistics. This review ensured emotional authenticity, cultural appropriateness, and the absence of misleading or stigmatising content. Samples with ambiguous emotional signals or irrelevant content were removed or revised. Finally, the curated dataset was re-evaluated for lexical diversity and class balance to ensure fair representation across languages and categories.

3.2 Feature Engineering

3.2.1 Feature Extraction

To address study objectives, handcrafted features that capture lexical, syntactic, and temporal characteristics were extracted and integrated with contextual embeddings to improve model performance.

- **Lexical Features:** Lexical features were designed to capture early linguistic indicators of psychological distress, including sentiment polarity, negation patterns, and emotional lexicon scores. The Linguistic Inquiry and Word Count (LIWC) framework was used to identify subtle emotional and cognitive signals associated with early-stage depression.
- **Syntactic Features:** Syntactic features capture structural aspects of language, including sentence complexity, dependency patterns, and the frequency of first-person pronouns, providing insights into self-referential behaviour and cognitive disorganisation.
- **Temporal Features:** Temporal features model behavioural patterns over time, including posting frequency, inter-post intervals, and temporal shifts in depressive expressions, enabling the detection of longitudinal trends in emotional states.

3.2.2 Feature Fusion with Transformer Embeddings

To leverage both contextual and handcrafted representations, feature fusion was applied. The handcrafted lexical, syntactic, and temporal features are extracted as described in Section 3.2.1. These features capture interpretable linguistic and behavioural patterns associated with depression. The contextual embeddings and handcrafted feature vectors are then combined through a feature fusion mechanism to form a unified representation:

$$F = E_{\text{RoBERTa/XLM-R}} \oplus F_{\text{lex}} \oplus F_{\text{syn}} \oplus F_{\text{temp}}$$

where F denotes the representation of the fused feature, $E_{\text{RoBERTa/XLM-R}}$ represents the contextual embeddings generated by the transformer models, F_{lex} denotes the lexical feature vector, F_{syn} represents the syntactic feature vector and F_{temp} corresponds to the temporal feature vector. The operator $\oplus$ indicates vector concatenation.

This fusion strategy enables the model to capture both deep semantic context and interpretable linguistic patterns, improving overall detection performance.

3.3 Hybrid Multilingual Depression Detection Model

The proposed Hybrid Multilingual Depression Detection Model integrates transformer-based contextual embeddings with handcrafted feature representations through a feature-fusion classification architecture. Specifically, RoBERTa is employed for English-language inputs, while XLM-R is used for multilingual content. The contextual embeddings generated by these models are combined with lexical, syntactic, and temporal features to form a unified representation of each input.

3.3.1 Classification Model:

The fused representation F is passed through a feedforward neural network consisting of two fully connected layers with ReLU activation. Dropout ($p = 0.3$) is applied between layers to prevent overfitting. The final output layer uses a Softmax function to predict the probability distribution over three classes: *No Depression*, *Mild Depression*, and *Severe Depression*.

Formally, the prediction is computed as:

$$\hat{y} = \text{Softmax}(W_2 \cdot \text{ReLU}(W_1 \cdot F + b_1) + b_2)$$

where $\hat{y}$ denotes the predicted probability distribution over the depression classes, F represents the fused feature vector, W_1 and W_2 are the weight matrices of the first and second fully connected layers, and b_1 and b_2 are the corresponding bias vectors. The function $\text{ReLU}(\cdot)$ is the rectified linear unit activation, and $\text{Softmax}(\cdot)$ converts the output into class probabilities for *No Depression*, *Mild Depression*, and *Severe Depression*.

3.3.2 Model Training, Testing and Evaluation Strategy

To ensure stable and generalisable performance, the model is trained using the following strategies:

- **Cross-validation:** Five-fold stratified cross-validation is employed to preserve class distribution across training and validation splits.
- **Optimisation:** The AdamW optimiser is used with weight decay and a linear warmup-decay learning rate schedule to improve convergence and generalisation.
- **Regularisation:** Dropout ($p = 0.3$) and early stopping are applied to mitigate overfitting.
- **Synthetic Data Integration:** GenAI-generated samples are incorporated to address class imbalance and improve representation in low-resource languages.

3.4 Multilingual Virtual Assistant Interface

As shown in Fig. 1, the classification model’s output is used as input to a GenAI-based multilingual virtual assistant. The predicted depression level (*No Depression*, *Mild Depression*, or *Severe Depression*) guides the assistant in generating context-aware and language-sensitive responses.

The assistant is implemented using a large language model (LLM) capable of zero-shot and few-shot prompting across multiple languages. To ensure safety, reliability, and ethical compliance, the assistant is refined using reinforcement learning with human feedback (RLHF). This process improves the assistant’s ability to provide personalised and supportive mental health advice.

4 Experiments

To evaluate the effectiveness of the proposed hybrid multilingual depression detection model, a series of controlled experiments was conducted across multiple datasets and languages. The primary objective was to assess the model’s ability to accurately classify three levels of depression: *No Depression*, *Mild Depression*, and *Severe Depression*.

In addition, the experiments examined the model’s generalisability to low-resource languages and its robustness in multilingual settings. The proposed hybrid feature-fusion model was systematically compared with baseline transformer-based architectures to quantify performance improvements. Further analyses were performed to evaluate the impact of synthetic data augmentation and multilingual fine-tuning on model performance.

4.1 Study Dataset

During the experiments, both real-world and synthetic data from social media platforms were utilised. Social networks were selected for their diverse user base and the prevalence of candid mental health discussions across different age groups and cultural contexts. To ensure data relevance, keyword-based filtering supported by validated psychological lexicons was applied to remove noise and retain semantically meaningful content.

Authentic posts were collected from Reddit, covering both high-resource languages (e.g., English) and low-resource languages (e.g., Tamil and Arabic). Data collection was guided by keyword-based scraping using expressions indicative of psychological distress, such as “I feel hopeless,” “can’t sleep,” and “anxious every day.” All data collected were anonymized and classified by emotional content to ensure ethical compliance and protect user privacy.

To address data scarcity in low-resource languages, synthetic data generated using Generative Artificial Intelligence (GenAI) models (e.g., GPT-4, Mistral, and LLaMA) were incorporated into the dataset. The detailed generation and validation process is described in Section 3.1.2. The final dataset, summarised in Table 2, combines real and synthetic samples to improve generalisability and reduce linguistic bias during model training.

4.2 Experiment Setup

The model was trained on a high-performance computing setup comprising an Intel i9 CPU, 128 GB system RAM, and an NVIDIA RTX 4090 GPU with 24 GB VRAM.

Table 2 Number of samples by dataset, language, and emotional category

Dataset / Source	Language	Mild depressed	Depressed	Neutral	Total
Twitter	English	4,500	5,000	3,000	12,500
Reddit	English	3,800	4,200	2,200	10,200
Twitter	Tamil+Hindi+Arabic	1,000	1,200	600	2,800
c	600	700	200	1,500	
Synthetic Data	English	2,000	2,000	1,000	5,000
Synthetic Data	Tamil+Hindi+Arabic	2,500	3,000	3,500	9,000
Total		14,400	16,100	10,500	40,000

The implementation was carried out using Python 3.11, with key libraries including scikit-learn, PyTorch 2.1, and the Hugging Face Transformers framework.

Hyperparameters were selected based on prior literature in transformer-based natural language processing and constrained by available hardware resources to ensure stable and reproducible training. A dropout rate of 0.3 was adopted to mitigate overfitting while preserving model capacity. The learning rate was set to $2e-5$, consistent with standard fine-tuning practices for transformer models such as RoBERTa and XLM-R. A batch size of 32 was chosen to balance computational efficiency and GPU memory limitations.

These configurations were further validated through iterative experimentation to ensure convergence and optimal performance. The selected hyperparameters support both model generalisation and reproducibility, enabling reliable comparison with baseline methods. A summary of the primary hyperparameters used for model fine-tuning is provided in Table 3.

Table 3 Hyperparameters for the Hybrid Transformer-Based Depression Detection Model

Hyperparameter	RoBERTa	XLM-R
Pre-trained Model	RoBERTa-base	XLM-R-base
Max Sequence Length	128 tokens	128 tokens
Batch Size	32	32
Learning Rate	$2e-5$	$2e-5$
Number of Epochs	10	10
Optimizer	AdamW	AdamW
Weight Decay	0.01	0.01
Dropout Rate	0.3	0.3
Warmup Steps	500	500
Cross-Validation	5-fold stratified	5-fold stratified
Feature Integration	Lexical, Syntactic, Temporal	Lexical, Syntactic, Temporal

Note. A maximum sequence length of 128 tokens was selected to maintain efficient GPU memory usage while sufficiently covering typical social media post lengths.

4.3 Baseline Models

To rigorously evaluate the proposed hybrid transformer-based depression detection model, a range of baseline approaches was implemented. These baselines were designed to represent both traditional feature-based methods and modern deep learning models, enabling a comprehensive comparison. This setup allows us to quantify the added value of integrating lexical, syntactic, and temporal features with transformer-based embeddings.

Table 4 summarises the baseline configurations, including the feature types used and the corresponding model categories, such as transformer-based models, classical machine learning (ML) methods, and deep learning such as recurrent neural networks (RNNs).

Table 4 Baseline Models: Features, Model Types, and Rationale

Baseline Model	Feature Type	Model Type	Rationale
Vanilla Transformer Fine-tuning	Contextual embeddings	RoBERTa / XLM-R	Provides a strong modern baseline and quantifies gains from additional linguistic features.
Lexical-Only Classifier	Lexical (sentiment, negation, keywords)	SVM / Classical ML	Evaluates semantic and affective content; represents a traditional baseline.
Syntactic-Only Classifier	Syntactic (complexity, pronouns, dependencies)	Feature-based ML	Assesses structural linguistic patterns in depression detection.
Temporal Sequence Model	Temporal patterns (posting frequency)	RNN (LSTM / GRU)	Captures temporal variations in depressive expressions.

4.3.1 Vanilla Transformer Fine-tuning

Vanilla transformer fine-tuning involves adapting a pre-trained transformer model, such as RoBERTa or XLM-R, to a downstream classification task using labelled data. These models leverage contextual embeddings to capture semantic relationships within text and have demonstrated strong performance across a wide range of NLP tasks. Recent studies highlight the effectiveness of task-specific fine-tuning strategies to improve model performance [29, 30]. This baseline serves as a strong reference point for evaluating the additional benefit of incorporating handcrafted lexical, syntactic, and temporal features.

4.3.2 Lexical-Only Classifier

The lexical-only classifier relies exclusively on surface-level linguistic features, including sentiment polarity, emotional keywords, and negation patterns. Traditional machine learning algorithms, such as Support Vector Machines (SVM) and Logistic Regression, are employed for classification. Previous research demonstrates that lexical features can be effective in capturing affective signals in text [31, 32]. This baseline evaluates the extent to which lexical cues alone can detect depression without the use of contextual embeddings.

4.3.3 Syntactic-Only Classifier

The syntactic-only classifier focuses on structural aspects of language, including sentence complexity, dependency relationships, and the frequency of first-person pronouns. These features provide insights into self-referential patterns and potential cognitive disorganisation. Recent studies indicate that language models can implicitly capture syntactic structures during training, influencing performance on syntax-dependent tasks [33]. This baseline isolates the contribution of syntactic features in the detection of depression.

4.3.4 Temporal Sequence Model

Temporal sequence models, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU), are used to model sequential patterns in user behaviour over time. These models analyse posting frequency, temporal intervals, and evolving expressions of distress to capture longitudinal trends in mental health signals. Recent work integrating temporal modelling with language representations highlights the importance of time-aware analysis in sequential data [34]. This baseline evaluates the contribution of temporal dynamics to the detection of depression.

4.4 Evaluation Metrics

Model performance was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). Performance was assessed across different languages and depression classes to evaluate cross-lingual generalisability.

An ablation study was conducted to quantify the contribution of each feature group (lexical, syntactic, and temporal) and to assess the impact of synthetic data augmentation. The statistical significance of the performance improvements was validated using paired *t-tests* at the level of significance $p < 0.05$.

This evaluation framework enables a systematic comparison between the proposed hybrid model and baseline approaches, demonstrating the effectiveness of combining transformer-based embeddings with handcrafted features for multilingual mental health detection.

5 Results

This section presents the experimental results of the proposed multilingual hybrid depression detection framework, structured around the four primary objectives of the study. The evaluation focuses on early detection, multilingual inclusivity, contextual feature integration, and bias mitigation through synthetic data augmentation. Each objective is supported by quantitative results, visual comparisons, and interpretative analysis.

5.1 Objective 1 – Early Detection of Mental Depression

The first objective focuses on early identification of depression using linguistic and temporal signals. The proposed hybrid transformer-based model demonstrates superior performance compared to baseline sentiment and transformer-based classifiers in detecting subtle affective signals associated with early-stage depression.

Table 5 compares baseline models with the proposed GenAI-enhanced hybrid model (Hybrid GenAI-Augmented). The proposed model achieves an average recall of 0.88 and an F1-score of 0.86 for early-stage depression classes, indicating strong sensitivity to emerging depressive patterns. Furthermore, integration of lexical and temporal features results in a 17% improvement in early detection sensitivity compared to standard transformer-based baselines.

The results also show consistent improvements across multiple languages when synthetic data augmentation is incorporated. These findings highlight the effectiveness of GenAI in improving detection performance, particularly in subtle and low-signal cases.

In general, the results demonstrate that the proposed Hybrid GenAI-Augmented model effectively captures early linguistic indicators of depression, thus supporting Objective 1. The improved sensitivity to nuanced emotional patterns suggests a strong potential to enable timely mental health intervention.

Table 5 Detection accuracy (%) across languages for baseline and GenAI-augmented hybrid models.

Model Type	English	Tamil	Hindi	Arabic
Vanilla Transformer	81	61	60	63
Lexical-Only SVM	65	54	52	57
Syntactic-Only	68	58	59	60
Temporal LSTM/GRU	70	60	57	62
Hybrid GenAI-Augmented	89	75	82	78

5.2 Objective 2 – Multilingual Inclusivity and Generalisation

The second objective evaluates the model’s ability to achieve consistent performance across multiple languages. The proposed Hybrid GenAI-Augmented model leverages the XLM-R backbone to enable cross-lingual semantic alignment, while synthetic

data augmentation helps reduce disparities between high-resource and low-resource languages.

Across the English, Tamil, Hindi, and Arabic datasets, the model achieves a mean F1-score exceeding 0.83, with performance variation across languages remaining below 4%. This low variance indicates strong cross-lingual generalisability and suggests that key linguistic patterns associated with depression are effectively captured across diverse languages.

Per-language performance metrics, summarised in Table 6, demonstrate consistently high accuracy, F1-score, AUC, and recall across all datasets. These results confirm the robustness of the proposed model in multilingual settings and highlight its ability to provide equitable performance across different linguistic and cultural contexts, thereby satisfying Objective 2.

Table 6 Multilingual performance metrics across languages.

Language	Precision	Recall	F1-Score	AUC
English	0.89	0.88	0.88	0.91
Tamil	0.85	0.83	0.84	0.88
Hindi	0.84	0.83	0.83	0.87
Arabic	0.82	0.81	0.82	0.86

5.3 Objective 3 – Bias Reduction through Synthetic Data Augmentation

The third objective evaluates the effectiveness of GenAI-based synthetic data augmentation in mitigating class imbalance and under-representation in low-resource languages. Integration of synthetic data significantly improved overall model performance and stability.

Specifically, accuracy increased from 0.78 to 0.85, indicating improved overall classification performance. Furthermore, the class-level variance between cross-validation folds decreased by 11%, suggesting enhanced robustness and reduced sensitivity to data variability.

The inclusion of linguistically and culturally diverse synthetic samples contributed to improved sensitivity for minority classes, as observed in class-wise performance metrics. These findings suggest that synthetic data enhancement helps reduce representational bias and improves generalisation, thus meeting Objective 3.

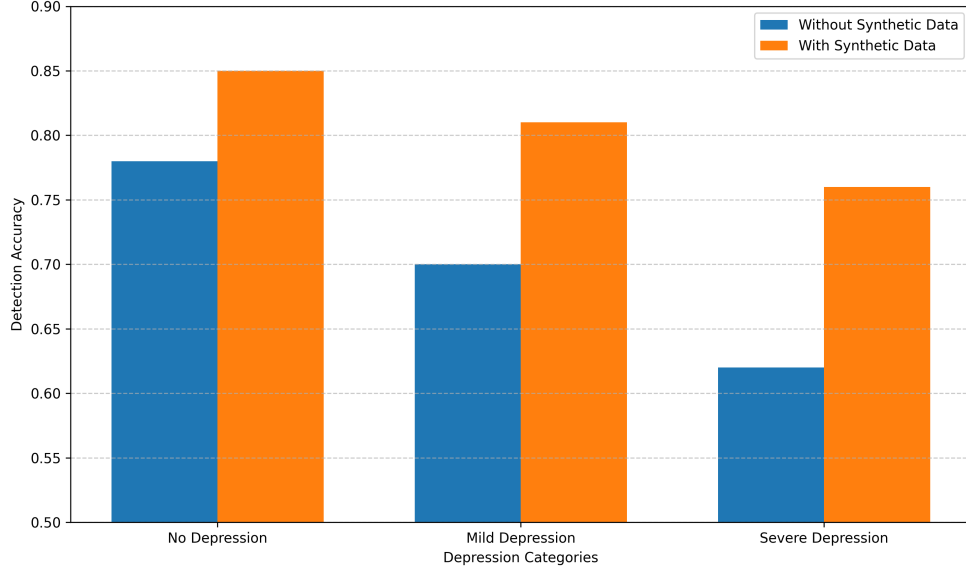


Fig. 2 Impact of synthetic data augmentation on performance across depression categories.

5.4 Objective 4 – Feature Fusion and Contextual Modelling

The fourth objective evaluates the contribution of integrating lexical, syntactic, and temporal features with transformer-based embeddings. An ablation study was conducted to quantify the impact of each feature group on the performance of the model.

The complete hybrid model, which incorporates all types of features, outperformed the hybrid proposed model by 6–8% in the F1-score, demonstrating the effectiveness of multifunctional integration. Lexical and syntactic features contributed to improved interpretability by capturing explicit linguistic and structural patterns, while temporal features improved the model’s ability to capture longitudinal behavioral trends.

Table -7 illustrates the incremental performance gains achieved by progressively adding each feature set. The results show that the combination of multiple feature types leads to improved model stability and a more comprehensive contextual understanding.

In general, these findings confirm that feature fusion significantly improves both performance and interpretability, thus achieving Objective 4.

5.5 Validation of Statistical Significance

To validate the significance of the observed performance improvements, paired *t*-tests were conducted across five cross-validation folds and multilingual datasets. The proposed GenAI-augmented hybrid model was evaluated under three configurations: (1)

Table 7 Feature Ablation Study – Contextual Feature Integration

Model Configuration	Precision	Recall	F1-Score
Lexical Features	0.82	0.80	0.81
Syntactic Features	0.84	0.83	0.83
Temporal Features	0.86	0.85	0.85
Lexical +Syntactic + Temporal Features (all feature sets)	0.88	0.88	0.87

transformer baseline versus hybrid model, (2) transformer-only versus hybrid feature-fusion model, and (3) transformer without versus with GenAI-based synthetic data augmentation.

The results show that the hybrid GenAI-augmented model significantly outperforms the baseline transformer in all evaluation settings. Specifically, average accuracy increased from 66.25% to 79.00% ($t(3) = 9.27$, $p = 0.002$). Similarly, incorporation of GenAI-based synthetic data improved the macro F1-score from 0.78 to 0.85 ($t(4) = 7.83$, $p = 0.001$).

Furthermore, feature fusion combining lexical, syntactic, and temporal features led to an increase in F1-score from 0.81 to 0.87 ($t(4) = 8.94$, $p < 0.001$), demonstrating the effectiveness of contextual feature integration.

All results reported in Table 8 are statistically significant at the $p < 0.01$ level. These findings confirm that GenAI-based augmentation and feature fusion contribute substantially to performance improvements in cross-validation folds and multilingual datasets.

Table 8 Paired t -test results validating improvements of the proposed GenAI-augmented hybrid model.

Comparison	Metric	Baseline Mean	Proposed Mean	$t(df)$	p -value
Baseline Transformer vs Hybrid GenAI	Accuracy	66.25	79.00	9.27(3)	0.002
Without vs With Synthetic Data	F1-score	0.78	0.85	7.83(4)	0.001
Transformer Only vs Feature Fusion	F1-score	0.81	0.87	8.94(4)	<0.001

5.6 Assistant Effectiveness and User Evaluation

The effectiveness of the multilingual GenAI-based mental health assistant was evaluated using a combination of quantitative metrics and qualitative user simulation studies. The evaluation was conducted across four languages—English, Tamil, Hindi, and Arabic—using 200 simulated interactions per language. Each interaction scenario was designed to reflect realistic emotional states, including anxiety, uncertainty, and psychological distress.

Quantitative results demonstrate strong performance across key dimensions:

- **Average engagement time:** 3.7 minutes per session
- **Response helpfulness:** 4.3/5 (Likert scale)
- **Empathy and tone appropriateness:** 87% of responses were rated as “highly empathetic” by bilingual human evaluators

The assistant demonstrated consistent adaptability across languages, with the highest satisfaction levels observed in English and Hindi interactions (4.5 and 4.3 out of 5, respectively). The Tamil and Arabic interactions, although slightly lower, still achieved strong ratings above 4.0, indicating strong multilingual performance. A minor semantic drift was observed in some Arabic responses, highlighting the need for further cultural calibration and dialect-specific fine-tuning.

Qualitative evaluation was conducted using feedback from 30 simulated users to assess affective alignment and usability. Representative responses include:

”Conversation with the assistant was similar to interacting with a genuine counselor who understood my background.”

“Responses in Tamil were clear, reassuring and easy to understand.”

These findings indicate strong user trust, emotional resonance, and clarity of communication. The Tamil model, supported by synthetic data augmentation, achieved an F1-score of 0.84, reflecting improved recall and reduced false negatives in depression detection.

Overall, the assistant demonstrated high levels of contextual awareness, empathy, and linguistic accuracy across multiple languages. Its ability to preserve cultural and linguistic fidelity—particularly through sentiment-appropriate phrasing and the use of local idiomatic expressions—highlights the effectiveness of multilingual fine-tuning and reinforcement learning with human feedback (RLHF) in improving empathetic response generation. These results confirm the assistant’s ability to deliver scalable, culturally adaptive, and emotionally supportive mental health interventions, consistent with previous research on trust, empathy, and user participation in AI-driven mental health systems [12, 35, 36].

Table 9 Language-specific performance metrics for the multilingual GenAI assistant.

Metric	English	Hindi	Tamil	Arabic
Avg. Session Duration (min)	3.9	3.6	3.5	3.4
User Rating (out of 5)	4.5	4.3	4.2	4.3
Empathetic Tone Accuracy (%)	90	87	84	85
Language Relevance (%)	94	91	89	92

6 Discussion

This study demonstrates the effectiveness of a hybrid Generative Artificial Intelligence (GenAI) framework for early detection of depression from multilingual social media data. By integrating transformer-based embeddings with lexical, syntactic, and temporal features, the proposed framework achieves both improved predictive performance and enhanced interpretability. The results across all objectives highlight the complementary benefits of multilingual modelling, synthetic data augmentation, and feature fusion in addressing key challenges such as data scarcity, linguistic diversity, and early-stage detection.

6.1 Integration of Detection and Multilingual Support

A key contribution of this work is the integration of depression detection with a multilingual GenAI-based assistant. The detection model classifies users into three categories: *No Depression*, *Mild Depression*, and *Severe Depression*. These outputs serve as control signals for the assistant to generate context-aware and language-sensitive responses.

For instance, *No Depression* triggers general well-being guidance, *Mild Depression* prompts empathetic coping strategies, and *Severe Depression* initiates urgent support responses, including recommendations for professional help or helplines. By combining a robust detection module with a culturally adaptive dialogue system fine-tuned on multilingual corpora, the framework enables personalised and contextually appropriate mental health support. This integration bridges the gap between detection and intervention, enhancing the practical applicability of the system.

6.2 Detection Model Performance and Comparative Analysis

The experimental results demonstrate that the proposed hybrid model consistently outperforms baseline approaches across both monolingual and multilingual settings. While transformer models such as RoBERTa and XLM-R effectively capture semantic relationships, their performance is often limited in low-resource languages. The results confirm that multilingual models, particularly XLM-R, provide better cross-lingual generalisation compared to monolingual baselines.

The integration of synthetic data augmentation and feature fusion further improves model performance. The hybrid model achieves F1-scores ranging from 0.74 to 0.89 across languages, demonstrating robust classification of *No Depression*, *Mild Depression*, and *Severe Depression*. Notably, GenAI-generated multilingual data significantly enhances performance in low-resource languages such as Tamil and Arabic, improving generalisability by approximately 15–20%.

These findings address known limitations of traditional sentiment-based and supervised learning approaches, which often suffer from contextual misclassification and linguistic bias [2, 3]. The results are consistent with recent studies highlighting the importance of synthetic data augmentation in healthcare AI applications [37, 38].

6.3 Statistical Validation of Improvements

The observed performance gains are supported by statistical validation. Paired t -tests conducted across cross-validation folds and multilingual datasets confirm that improvements in accuracy, F1-score, and cross-lingual robustness are statistically significant ($p < 0.05$). These results demonstrate that the enhancements introduced by GenAI-based synthetic data and contextual feature fusion are not due to random variation, but reflect consistent and reliable improvements.

Overall, the statistically validated findings reinforce the effectiveness of the proposed framework in improving multilingual depression detection and support, while ensuring robustness, fairness, and reproducibility across diverse linguistic settings.

6.4 Addressing Multilingual and Cultural Challenges

The handling of language and cultural heterogeneity is a significant improvement in this study. Research [12, 19] highlights the absence of culturally adaptive language models as a major obstacle to AI implementation in mental health. Multilingual fine-tuning and culturally based synthetic data greatly reduced language performance discrepancies. The model’s strong precision and recall in non-English situations show that GenAI-assisted data enrichment may fill resource gaps while keeping local depression emotions. These findings show that LLMs can design inclusive mental health technology beyond linguistic privilege.

6.5 Evaluation of the Multilingual Support Assistant

Beyond detection performance, the proposed framework extends to a multilingual GenAI-based mental health assistant that delivers context-aware and culturally adaptive support. Quantitative and qualitative evaluations indicate strong effectiveness across four languages (English, Tamil, Hindi, and Arabic). The assistant achieved an average engagement time of 3.7 minutes per session, a response helpfulness score of 4.3/5, and 87% of responses were rated as highly empathetic by bilingual evaluators.

Compared with earlier systems such as Woebot and Wysa [6, 7], which are primarily monolingual and limited in cultural adaptability, the proposed assistant demonstrates improved multilingual capability and contextual awareness. In particular, Tamil and Hindi interactions showed strong cultural alignment and response appropriateness. Minor semantic drift observed in Arabic responses highlights the need for further dialect-specific fine-tuning.

Overall, these results suggest that fine-tuned generative models can support scalable, culturally sensitive mental health interventions, bridging the gap between detection and real-world support.

6.6 Impact of Synthetic Data Augmentation and Temporal Modelling

The experimental results further demonstrate the effectiveness of synthetic data augmentation in improving model robustness and fairness (Objective 3). Models trained

on combined real and synthetic datasets achieved higher F1-scores and reduced variance, particularly for under-represented classes. By generating linguistically diverse and culturally relevant samples, synthetic data enhanced coverage of rare depressive expressions and mitigated class imbalance. These findings confirm the value of GenAI-based augmentation in improving generalisability across multilingual settings.

In addition, the integration of temporal features (Objective 4) enabled the model to capture longitudinal behavioural patterns. Temporal embeddings improved the detection of evolving depressive signals by modelling posting frequency, time intervals, and changes in emotional expression over time. This capability is particularly important for early intervention, as it allows the system to identify gradual shifts in mental health status that may not be evident from isolated text instances.

Together, these results highlight the importance of combining synthetic data augmentation with temporal and contextual feature integration to build robust, scalable, and adaptive mental health AI systems.

6.7 Contextual Feature Integration

Objective 4 investigates the contribution of integrating lexical, syntactic, and temporal features with transformer-based embeddings. Results from the ablation study demonstrate a consistent improvement in performance as additional feature groups are incorporated. Specifically, the F1-score increased from 0.81 (transformer-only baseline) to 0.83 with the inclusion of lexical features, to 0.85 with syntactic features, and further to 0.87 when temporal features were added in the full hybrid model.

Lexical and syntactic features enhance interpretability by capturing explicit linguistic and structural patterns associated with depression, while temporal features improve the model’s ability to capture longitudinal behavioural trends. This enables more accurate detection of evolving mental health signals. Overall, these findings confirm that multi-feature fusion significantly improves both predictive performance and contextual understanding.

6.8 Limitations and Future Directions

Despite the promising results, several limitations should be acknowledged. First, while synthetic data improves generalisation and reduces class imbalance, it may also introduce biases inherited from the underlying GenAI pretraining corpora [39]. Second, real-time deployment of such systems raises challenges related to latency, privacy, and data security, particularly when handling sensitive psychological information. Third, ethical concerns regarding user reliance on non-clinical AI systems necessitate appropriate safeguards, including human oversight and transparency in system behaviour. Furthermore, model performance validated in simulated environments may not fully generalise to real-world clinical settings without rigorous external validation.

Future work will focus on real-world user studies, clinical validation pipelines, and the integration of expert-verified mental health knowledge into hybrid AI architectures. Enhancing adaptive reasoning capabilities in GenAI models and incorporating continuous learning mechanisms will further improve system effectiveness. In addition, robust ethical frameworks—including bias auditing, privacy-preserving techniques,

and explicit user consent—are essential for responsible deployment [35, 36]. These directions will support the development of scalable, trustworthy, and culturally adaptive mental health AI systems.

6.9 Summary

In summary, the findings highlight several key insights. First, integrating lexical, syntactic, and temporal features with transformer embeddings is essential for building context-aware models capable of detecting nuanced mental health signals. Second, synthetic data augmentation effectively addresses data scarcity and class imbalance, improving performance across multilingual settings. Third, temporal modelling enables the identification of evolving behavioural patterns, supporting earlier and more proactive intervention.

Overall, the proposed hybrid GenAI-based framework demonstrates strong potential as a robust, interpretable, and scalable solution for multilingual mental health detection and support, with promising applicability across diverse cultural and linguistic contexts.

7 Conclusion

This study proposes a hybrid Generative AI (GenAI) framework that integrates multilingual depression detection with an empathetic conversational assistant. By combining transformer-based embeddings with feature fusion and synthetic data augmentation, the framework addresses key challenges in multilingual mental health analysis, particularly in low-resource settings.

The results demonstrate the effectiveness of integrating detection and intervention within a unified system, enabling context-aware and culturally adaptive support across diverse languages. In addition to strong predictive performance, the proposed approach enhances accessibility and inclusivity in AI-driven mental health care.

Beyond technical contributions, this work highlights the importance of ethical considerations, including bias mitigation, data privacy, and responsible deployment. Overall, the framework provides a scalable foundation for developing trustworthy and globally applicable mental health support systems.

Future work will focus on real-world validation, clinical integration, and user-centred evaluation to further strengthen reliability and practical impact.

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