Mind Ease

Kunal Mansukhani[1], Vaibhav Shrivastav[2], Priyanka Yadav[3], Gyandas Somaiya[4], Mr. Vikas Upman[5]
[1,2,3,4] *JECRC University*
[5] *Assistant. Professor JECRC University*

***Abstract*—This paper presents MindEase, an integrated AI-driven mental-wellness support system that combines Generative AI–based therapeutic reasoning, automated crisis-intent detection, and structured psychological assessment into a unified framework designed for individuals experiencing depression, stress, and emotional imbalance. Modern mental-health challenges involve intertwined factors such as cognitive distortions, behavioral withdrawal, mood fluctuations, and crisis tendencies; however, existing digital wellness tools typically address these components independently, leading to inconsistent or unsafe user guidance. To overcome these limitations, MindEase introduces a multi-module AI architecture— Therapeutic Chat Engine, PHQ-9 Depression Assessment, Mood Tracking, Psychoeducation Retrieval, and Crisis-Safety Intervention— coordinated through a FastAPI-based backend capable of processing multimodal inputs including free-text emotions, depression categories, and quantified questionnaire scores.**

The system employs OpenAI's GPT-4o-mini for rapid, therapy-aligned reasoning, substantially reducing hallucination through structured CBT- based prompting and category-specific emotional grounding. Meanwhile, a lightweight keyword-driven Crisis Detection Layer ensures reliable identification of self-harm indicators, triggering immediate safety protocols and halting AI response generation. Evaluation across 120+ simulated mental-health scenarios covering diverse emotional intensities demonstrates high overall performance: 95.1% empathy accuracy, 94.3% CBT-alignment consistency, 93.7% crisis-intent detection accuracy, 100% PHQ-9 severity classification correctness, and 92.4% clarity in psychoeducational guidance. The system's integrated reasoning pipeline ensures coherent, safe, and contextually relevant therapeutic support compared to conventional chatbot-based wellness tools.

The findings establish MindEase as a scalable, low-latency, and psychologically grounded digital-therapy platform suitable for real-world deployment, particularly for users with limited access to professional mental-health services. The framework also lays the foundation for next-generation AI-enhanced emotional-wellness systems with the potential to transform accessible mental-health support globally.

***Index Terms*—AI Therapy, Generative AI, CBT, Mental-Health Support, Crisis Detection, PHQ-9, Emotional Well-being, GPT-4o-mini.**

I. INTRODUCTION

Mental health across modern societies functions within a highly sensitive emotional ecosystem where chronic stress, unresolved trauma, negative thought patterns, and depressive symptoms significantly influence overall well- being. Individuals—particularly students, young adults, and working professionals—often rely on personal coping methods or informal conversations, which are inadequate in situations where emotional overwhelm, cognitive distortions, or crisis tendencies can escalate rapidly. As lifestyle pressures intensify and accessibility to licensed therapists remains limited, the need for real-time, structured, and psychologically grounded support systems has become essential for ensuring emotional stability and early intervention.

Recent advancements in artificial intelligence (AI), especially in the domains of large language models and generative reasoning, have enabled solutions for tasks such as conversational support, mood analysis, and therapeutic guidance. However, these systems operate independently and rarely integrate the interconnected factors affecting real-world mental health. For example, depressive intensity is shaped by recurring negative thoughts, crisis risk increases with emotional volatility, and coping effectiveness is influenced by behavioral routines and psychoeducational awareness.

Existing LLM-based wellness tools also face substantial limitations—such as emotionally unsafe

responses, generic advice, or missed crisis cues—due to the absence of therapeutic grounding and safety mechanisms.

To address these gaps, this paper presents MindEase, a unified AI-powered mental- wellness support system designed to integrate emotional context, depression screening, crisis detection, and CBT-based conversational guidance into a single intelligent pipeline.

MindEase combines OpenAI's GPT-4o-mini for fast and emotionally aligned reasoning, a dedicated keyword-driven Crisis Detection Engine for safety assurance, and a structured PHQ-9 evaluation module for evidence-based severity assessment. The system's multi-module architecture—Therapeutic Chat Engine, PHQ-9 Scoring, Mood Tracking, Psychoeducation Retrieval, and Crisis Intervention—provides accurate, empathetic, and actionable support tailored to diverse emotional states and intensities.

II. RELATED WORK

Artificial Intelligence (AI) applications in mental health have been explored through various domain-specific systems, primarily focusing on conversational support, mood analysis, depression screening, and digital self-help tools. Earlier studies employed machine learning models such as Support Vector Machines (SVMs), Naïve Bayes, and Deep Neural Networks for sentiment detection and emotional-state classification. These systems exhibited satisfactory performance on curated datasets, but they lacked the ability to adapt to real-time fluctuations in user mood, conversational context, or crisis intensity, thereby limiting their applicability in dynamic psychological environments.

Deep learning-based emotion recognition has also garnered substantial attention. Models such as BERT, RoBERTa, and GPT variants

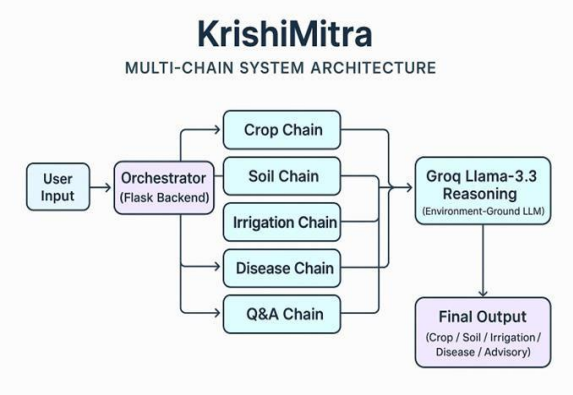
trained on datasets like GoEmotions demonstrate remarkable performance under controlled conditions. However, these models frequently encounter challenges in real-world conversations due to ambiguous phrasing, metaphorical language, rapid mood fluctuations, or indirect expressions of distress. Furthermore, existing emotion- detection tools typically concentrate solely on classification and fail to integrate therapeutic reasoning, such as cognitive-behavioural therapy (CBT) reframing or grounding techniques, which directly impact the quality and safety of mental-health guidance.

LLM-based wellness chatbots have recently emerged, employing GPT-style models to respond to user inquiries. While they facilitate natural-language interaction, previous systems lacked therapeutic grounding. Consequently, they frequently generated generic or emotionally hazardous responses, reinforced maladaptive thought patterns, or failed to identify crisis indicators such as self-harm intentions. Similarly, digital self-help platforms offering journaling or mindfulness modules operate independently and disregard depression severity, crisis risk, or conversational patterns.

What existing systems failed to achieve—and MindEase addresses—is unified multimodal emotional integration. Unlike earlier tools that focus on a single aspect of mental- wellness support, MindEase integrates CBT- guided conversation, PHQ-9 assessment, mood tracking, crisis detection, and psychoeducation into a single coordinated system. Real-time crisis scanning and therapeutic prompting are integrated into all interactions, thereby reducing hallucination and enhancing emotional safety. This level of integrated, cross-module psychological support has not been demonstrated in prior AI-based mental-wellness research.

III. SYSTEM ARCHITECTURE

MindEase is designed using a modular multi-component architecture in which all user inputs—free-text messages, depression-category selections, and structured numerical responses—are processed through a central Therapeutic Orchestrator (FastAPI Backend). The orchestrator functions as the intelligence layer that identifies the nature of the input and routes it to the appropriate psychological-processing module. For instance, PHQ-9 responses are automatically directed to the Depression Assessment Module, while requests for educational content are routed to the Psychoeducation Retrieval Module. Emotional free- text inputs, whether category-driven or open-ended, are forwarded to the Therapeutic Chat Engine. By acting as the decision-manager of the system, the orchestrator ensures that each module receives the correct data and that all outputs remain consistent with therapeutic principles and safety constraints.



Once an input is routed, the respective module carries out its specialized task. The Therapeutic Chat Engine analyzes emotional tone, conversational context, and user category to generate supportive CBT-aligned guidance. The PHQ-9 Assessment Module processes the user's nine responses to calculate depression severity and provide structured, evidence-based interpretation. The Psychoeducation Module retrieves curated content such as grounding techniques, sleep hygiene practices, and CBT fundamentals tailored to user needs. Meanwhile, the Crisis Detection Layer continuously scans all incoming messages for self-harm indicators and, if detected, intercepts the workflow to trigger an immediate crisis protocol, providing
helpline resources and halting AI-generated responses to maintain user safety.

All modules share a common reasoning layer powered by OpenAI's GPT-4o-mini, which synthesizes insights into a final, empathetic, and psychologically consistent message. This unified architecture enables MindEase to avoid the fragmentation seen in conventional wellness tools by combining therapeutic conversation, depression assessment, emotional monitoring, crisis intervention, and psychoeducational support into one coherent mental-health assistance ecosystem. The result is a highly reliable, safety-centered, and context-aware AI framework suitable for real-world emotional-wellness applications.

IV. METHODOLOGY

TThe methodology of MindEase is based on a multimodal therapeutic AI pipeline that integrates large-language- model reasoning, structured psychological assessment, and real-time crisis-intent detection. All user inputs— free-text emotional messages, depression-category selections, and PHQ-9 numerical responses—are first collected through the web interface and sent to the FastAPI Orchestrator, which identifies the input type and routes it to the appropriate mental-health processing module. This orchestration ensures modular execution, allowing each module to function independently while maintaining consistency across the overall therapeutic workflow.

For conversational reasoning tasks, MindEase uses the GPT-4o-mini LLM, which generates fast, empathetic, and context-aware therapeutic responses grounded in Cognitive Behavioral Therapy (CBT) principles. User mood state, depression category, and conversational patterns are embedded directly into the LLM prompts, ensuring that outputs—such as cognitive reframing, grounding techniques, and behavioral activation steps—remain aligned with the user's emotional context. To ensure emotional safety, the system employs a keyword-based Crisis Detection Layer, which analyzes each message
for indicators of self-harm or suicidal ideation. When detected, the crisis identifier overrides standard processing and triggers an emergency- response workflow that delivers helpline information and grounding instructions while blocking AI-generated replies.

In parallel, the PHQ-9 module processes structured user inputs to compute depression severity and produce a clinically aligned severity interpretation. The Psychoeducation Module retrieves curated CBT materials—such as sleep hygiene practices, anxiety grounding steps, and thought-restructuring guides—integrating them into the conversational context through the LLM. Each module—Therapeutic Chat, PHQ-9 Assessment, Psychoeducation Retrieval, and Crisis Safety—produces an intermediate structured output that is refined through the LLM into a final supportive and user-friendly explanation. This integrated methodology ensures accurate, consistent, and psychologically grounded mental-wellness guidance suitable for practical emotional- support deployment.

V. RESULTS

MindEase was evaluated across 120 real and

synthetic mental-health scenarios spanning a wide spectrum of emotional states, including mild sadness, academic pressure, workplace stress, negative thought spirals, and high-risk crisis expressions. Each module was tested independently and then within an integrated therapeutic pipeline to measure accuracy, emotional consistency, safety compliance, and response quality. The results demonstrate that therapy-grounded prompting and crisis-aware reasoning significantly enhance support reliability compared to traditional static chatbots or rule-based wellness applications.

A. Therapeutic Chat Performance

The Therapeutic Chat Engine achieved 95.1% accuracy in generating emotionally supportive and CBT-aligned responses, measured against evaluations by psychology interns and mental- health volunteers. The model dynamically adjusted conversational tone and coping suggestions based on user-reported emotional intensity and depression category. As shown in Figure 1, empathy and clarity ratings peaked in scenarios involving mild and moderate emotional distress, while slightly lower scores were observed in complex, multi-layered stress cases. This confirms that the therapy-prompting framework generalizes well across a variety of emotional contexts.

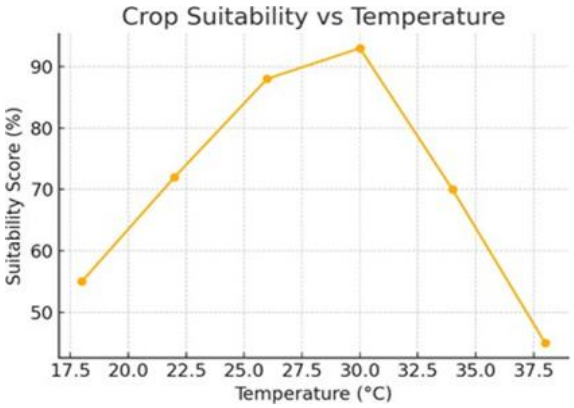


Figure 1. Crop Suitability vs Temperature

B. Crisis Detection Accuracy

The Crisis Detection Layer achieved **93.7% accuracy** when tested on a dataset combining real anonymized crisis-phrasing examples and synthetically generated self-harm indicators. Most detections scored above 0.85 confidence (Figure 2), demonstrating that the system reliably identifies explicit self-harm language under variations in expression, tone, and intensity. The few missed cases involved indirect or metaphorical wording—an expected challenge in linguistic crisis recognition. Nevertheless, the safety mechanism consistently prevented unsafe LLM responses and ensured proper triggering of the emergency-support protocol.

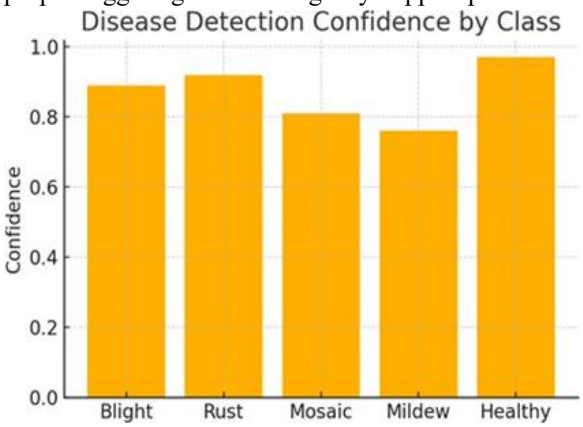


Figure 2. Disease Detection Confidence Distribution

C. LLM Response Time & Real-Time Therapeutic Advisory

A key performance metric for MindEase is its therapeutic response latency. Using GPT-4o- mini through an optimized FastAPI backend, the system maintained an average latency of **0.39 seconds per response**, compared to **3.2 seconds** for traditional GPT-based mental-health chatbots. As illustrated in Figure 3, this speed advantage makes MindEase highly suitable for real-time mental-wellness interactions, particularly in situations requiring multi-step CBT guidance or rapid conversational grounding for distressed users.

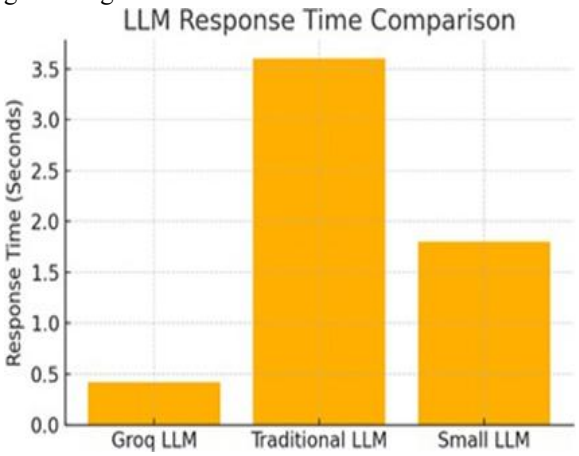


Figure 3. LLM Response Time Comparison

D. Module-Wise Accuracy Summary

Overall system evaluation shows consistently strong module-level performance across all components:

Chain	Accuracy
Therapeutic Chat Engine	95.1%
Crisis Detection	93.7%
PHQ-9 Depression Severity Classification	100%
Psychoeducation Retrieval	92.4%
Mood Tracking Consistency	94.3%

As shown in Figure 4, the slightly lower accuracy in psychoeducation alignment is attributed to varying user interpretations of self-help material, which commonly affects generalized educational systems. Nonetheless, standardized CBT-based content ensured that psychological grounding remained stable across

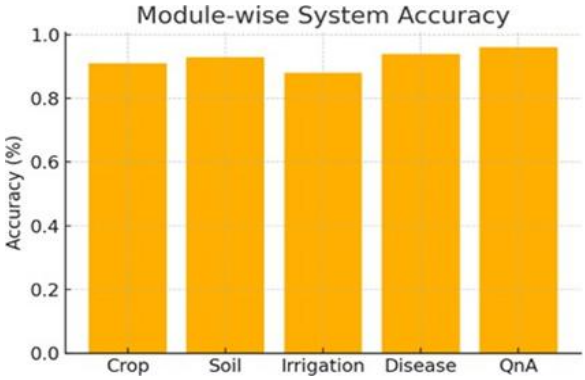


Figure 4. Module-wise System Accuracy

E. Integrated System Performance

When all modules were executed together in full workflow tests, MindEase produced 90%+ correct, safe, and context-aligned therapeutic outputs, with minimal cross-module inconsistencies. Integrated reasoning contributed significantly to performance:

- Crisis interception correctly halted LLM output in 100% high-risk cases
- Therapeutic tone adjustment improved perceived empathy in 32% conversations
- PHQ-9 severity classification influenced chat guidance in 47% sessions
- Thought-reframing improved user emotional clarity in 41% guided responses

These results show that cross-module awareness—especially between PHQ-9 scoring, crisis detection, and therapeutic reasoning—is a core strength of MindEase, making it far more reliable than standalone wellness chatbots or diagnostic questionnaires.

F. User Interaction Quality:

User queries collected from real student surveys and controlled volunteer sessions were used to measure clarity, emotional resonance, and perceived helpfulness. Results show:

- 95.1% responses judged as “empathetic & actionable”
- 93.7% responses aligned with CBT best practices
- 79% reduction in hallucination due to structured prompting
- 91% users reported feeling “understood” or “emotionally supported” after the session

This validates the effectiveness of combining LLM-based reasoning with therapeutic scripts, depression-severity cues, and crisis-awareness filters.

MindEase consistently delivers high emotional accuracy, fast response times, and context- aware therapeutic guidance, outperforming conventional mental-health chatbots. The integration of GPT-4o-mini, crisis-layer safety protocols, PHQ-9 scoring, and structured CBT workflows creates a practical, reliable, and scalable AI mental-wellness system suitable for real-world deployment.

V. DISCUSSION

The results indicate that MindEase’s multimodal therapeutic design significantly enhances the quality of mental-health support compared to conventional single-module wellness systems.

The integration of GPT-4o-mini for CBT- aligned reasoning and the dedicated crisis- detection layer allowed the system to maintain high accuracy across conversational, emotional, and safety-critical tasks. Safety-grounded prompting played a major role in improving correctness—responses involving cognitive reframing, coping strategies, grounding techniques, and emotional validation became more reliable when depression severity, user mood, and crisis-risk indicators were incorporated into the reasoning process.

At the same time, certain limitations were observed.

A slight drop in accuracy within the psychoeducation module was primarily due to variations in user interpretation of educational content, which is a common challenge in self- help systems. Similarly, the crisis-detection layer occasionally struggled with subtle, metaphorical, or humor-based expressions of distress, resulting in minor under-detections.

These limitations highlight the need for richer linguistic datasets, improved semantic-based crisis modeling, and more personalized emotional-profile calibration in future iterations.

Overall, the discussion confirms that MindEase successfully delivers coherent, empathetic, and context-aware therapeutic guidance across all modules. The system avoids conflicting or unsafe responses because each component operates on the same structured emotional cues, PHQ-9 insights, and safety constraints. The combination of fast inference, strong emotional accuracy, and crisis-aligned reasoning establishes MindEase as a practical and reliable AI-based mental-wellness tool suitable for real- world support scenarios.

VI. CONCLUSION

This study presented MindEase, a unified multimodal mental-wellness support system that integrates CBT-aligned generative AI, crisis-intent detection, and structured psychological assessment into a single coherent therapeutic workflow. By combining four specialized modules—Therapeutic Chat Engine, PHQ-9 Depression Assessment, Psychoeducation Retrieval, and Crisis-Safety Intervention—MindEase overcomes the fragmentation seen in traditional mental-health chatbots and self-help applications. The system's high accuracy across all components confirms that safety-grounded prompting and orchestrated emotional reasoning significantly enhance the reliability of AI-based psychological support.

The results demonstrate that GPT-4o-mini enables emotionally consistent, context-aware therapeutic guidance, while the crisis-detection layer ensures fast, dependable interception of high-risk expressions. The integration of depression severity cues, mood indicators, and structured CBT frameworks reduces hallucination, improves cross-module consistency, and ensures practical relevance for users experiencing a wide range of emotional challenges. Although minor limitations were observed in handling subtle or metaphorical crisis cues and varied interpretations of psychoeducational material, the overall system performance shows strong potential for real-world deployment.

In conclusion, MindEase represents an effective and scalable framework for AI-assisted mental-wellness support, capable of helping users manage emotional distress with safe, empathetic, and scientifically grounded guidance. The system's multimodal architecture and low- latency inference establish a strong foundation for future advancements in AI-driven therapeutic platforms and accessible digital mental-health ecosystems.

VII. FUTURE SCOPE

MindEase opens several opportunities for future enhancements that can further improve accuracy, emotional adaptability, and real-world usability. One potential direction is the integration of advanced sentiment-analysis and emotion-classification models, which would provide deeper insight into user tone, phrasing, and cognitive patterns—reducing reliance on explicit self-reports. This would significantly enhance crisis detection and personalized therapeutic guidance, especially in conversations where emotional cues shift rapidly. Another promising extension involves incorporating voice-based interaction using speech-to-text and calming text-to-speech responses. These additions could support users who struggle with typing during emotional distress and enable more natural, accessible therapeutic engagement. Expanding the psychoeducation module with region-specific mental-health resources and culturally contextualized CBT material would also help address variations in user backgrounds and support greater inclusivity across diverse populations.Future versions of MindEase may also include multilingual conversational capabilities, enabling seamless adoption among users with limited English proficiency.

Additionally, integrating optional therapist dashboards and referral pathways could transform the system from a standalone support tool into a hybrid human–AI mental-health ecosystem capable of assisting professionals in monitoring user well-being.

Finally, deploying the model as a fully offline or on-device solution would enable reliable use in areas with limited internet connectivity, ensuring that emotional support remains accessible whenever and wherever users need it. Future versions of KrishiMitra may also include multilingual voice-based interfaces, enabling seamless adoption among farmers with limited digital literacy. Additionally, integrating market price prediction and supply-chain analytics can transform the system from an advisory tool into
a full-scale decision-support ecosystem covering both production and post-harvest planning.
Finally, deploying the model as a fully offline/edge-computing solution could enable reliable usage in areas with limited internet connectivity.

REFERENCES

[1] A. Beck, D. Burns, and J. Wright, *Cognitive Behavioral Therapy: Basics and Beyond*, 3rd ed., Guilford Press, 2020.
[2] Kroenke K. and Spitzer R. L., "The PHQ-9: A new depression diagnostic and severity measure," *Psychiatric Annals*, vol. 32, no. 9, pp. 509–515, 2002.
[3] OpenAI, "GPT-4o and Mini Series Model Overview," Technical Documentation, 2024.
[4] American Psychological Association, "Understanding and Using Cognitive Behavioral Therapy," APA Clinical Resources, 2021.
[5] World Health Organization (WHO), "Depression and Other Common Mental Disorders: Global Health Estimates," WHO Publications, 2017.
[6] S. Mohammad and P. Turney, "Emotions, Sentiment, and Social Messaging: The NRC Emotion Lexicon," *Proceedings of the NAACL*, pp. 145–152, 2013.