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Research Article

Emotion-Aware AI Chatbots for Mental Health Support in Low-Resource Public Health Systems: A Case Study from Ghana

Evans Ankomah[1] 📵, **Regina Esi Turkson[2, *]** 📵

[1]IT Training and Support Section, University of Cape Coast, Cape Coast, Ghana
[2]Department of Computer and Information Technology, University of Cape Coast, Cape Coast, Ghana

Abstract

Mental health conditions are on the rise globally, yet many low-resource countries face systemic barriers such as stigma, underfunding, and a severe shortage of professionals to provide adequate care. This paper presents the design, implementation, and evaluation of an emotion-aware AI chatbot for mental health support within Ghana's public health context, aiming to bridge the mental health treatment gap. Leveraging deep learning for emotion detection and integrating a generative language model (GPT-3.5), the system delivers culturally relevant responses to users exhibiting symptoms of emotional distress. The study restructured the International Survey on Emotion Antecedents and Reactions (ISEAR) dataset into a 5-emotion model (Joy, Fear, Anger, Sadness, Neutral) to improve classification accuracy. A Convolutional Neural Network (CNN) emerged as the top-performing classifier (76.4% accuracy), outperforming LSTM, BiLSTM, and GRU models. This classifier was integrated with GPT-3.5 to enable context-aware, empathetic interactions. Field testing with 311 participants in Ghana revealed high satisfaction: 89% praised usability, 81% affirmed cultural relevance, and 78% reported emotional support. Notably, 66% felt encouraged to seek professional care, demonstrating the chatbot's potential as a gateway to formal mental health services. The system's anonymity and 24/7 accessibility addressed key barriers like stigma and resource limitations. The findings suggest that emotion-aware chatbots can complement mental health services in under-resourced settings and offer an innovative pathway for public health outreach. Future work will expand language options and crisis protocols. This research contributes a scalable, cost-effective model for global public health, emphasizing cultural adaptation and emotion-aware AI as critical tools in mental health innovation.

Keywords

Mental Health, Chatbot, Emotion Detection, Deep Learning, AI in Public Health, Ghana, GPT-3.5, Low-Resource Settings

1. Introduction

Mental health has become a critical public health issue worldwide, particularly in low- and middle-income countries (LMICs), where access to professional care is severely limited by stigma, geography, cost, and systemic underfunding. The World Health Organization (WHO) estimates that one in ten individuals globally need mental health care, yet in

low-income countries, there are only two mental health professionals for every 100,000 people [1]. In Ghana, approximately 2.4 million people suffer from mental illness, but only 2% of them receive psychiatric support [2, 3]. Structural challenges—including underfunding (only 1.4% of the national health budget is allocated to mental health), outdated policy frameworks, and a shortage of qualified personnel—compound the problem [3].

In response to these limitations, mental health care in Ghana often relies on informal providers such as traditional and faith-based healers, which vary in quality and effectiveness [4]. Meanwhile, community-based surveys show high psychological distress levels, with nearly 30% of Ghanaians reporting mental distress and 12.7% meeting the criteria for depressive disorders [3]. These data underscore the need for scalable and accessible solutions to support the nation's mental health infrastructure.

Chatbot systems have emerged as promising digital tools to address mental health issues, offering anonymity, 24/7 availability, and affordability. Globally, systems like Woebot, Wysa, and Tess have shown effectiveness in reducing symptoms of depression and anxiety [5, 6]. In Ghana, research has suggested that both mental health professionals and patients are open to using mobile-based or internet-enabled interventions for mental health management [7]. Chatbots are capable of proactive emotional engagement, reminder services, and empathetic responses, and can be trained to understand psychological triggers using deep learning techniques [8].

Despite their potential, existing chatbot systems are often Western-centric and lack cultural sensitivity or language adaptability for African contexts [9]. In Ghana, no existing framework robustly integrates localized emotion detection with generative Artificial intelligence (AI) to support mental health.

This research seeks to bridge this gap by developing and implementing an emotion-aware chatbot tailored to Ghana's public mental health landscape. The goal is to enhance access to care, address anxiety and depression, and complement the limited human resource capacity with AI-based support. In doing so, we contribute to the broader effort to reduce Ghana's mental health treatment gap and build resilient digital public health infrastructure.

2. Background and Related Work

2.1. Mental Health and the Rise of Digital Interventions

Mental health disorders represent a growing global concern, particularly in low- and middle-income countries (LMICs), where more than 75% of individuals with mental illness receive no treatment [1, 10]. The shortfall is largely due to limited human resources, stigma, and weak health infrastructure. In Ghana, only 2% of the estimated 2.4 million

people living with mental illness have access to professional care [3]. As a result, digital health innovations are increasingly seen as viable tools to extend care in under-resourced settings.

Among these, AI-powered chatbot systems have emerged as promising tools for delivering psychological support [7]. Chatbots offer round-the-clock availability, anonymity, and scalability—benefits particularly relevant in environments where human therapists are scarce. During the COVID-19 pandemic, chatbots helped triage mental health concerns and alleviate the burden on traditional care systems [11]. Additionally, mental health professionals in both high- and low-resource settings have expressed openness to using digital mental health interventions [5].

2.2. Chatbot Systems in Mental Health

Chatbots such as Woebot, Wysa, and Tess have been used effectively to help individuals manage anxiety, depression, and stress through structured, evidence-based interactions [6, 12]. These systems typically follow cognitive behavioral therapy (CBT) frameworks and use scripted or rule-based dialogues. While effective, they lack adaptability, and many fail to resonate with users from diverse cultural backgrounds.

Research by [9] that user feedback on mental health chatbots is generally positive, especially in terms of convenience and emotional safety. However, most existing systems are developed with Western populations in mind, raising questions about their cultural sensitivity and efficacy in African contexts [9].

2.3. Evolution of Conversational Agents

Conversational systems have evolved significantly—from early programs like Eliza in the 1960s to modern large language models such as GPT-3.5. These advances have improved chatbots' ability to handle natural language, maintain context, and demonstrate empathy. Today's chatbots are broadly categorized as:

1) Retrieval-based: Use pre-scripted responses and rule-based decision trees [13].
2) Generative-based: Use neural networks and deep learning to generate human-like responses dynamically [14].

Generative chatbots are particularly suited to mental health use cases due to their flexibility and capacity for personalization [15].

2.4. Emotion Detection and Cultural Adaptation

Emotion recognition plays a key role in enabling chatbots to deliver empathetic responses. Deep learning models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Bidirectional LSTM, and Gated Recurrent Units (GRU) have shown high performance in emotion classification tasks using datasets like ISEAR [16]. Simplifying

the dataset from seven to five emotion classes: Joy, Fear, Sadness, Anger (Anger + Guilt) and Neutral (Shame + Guilt) improves accuracy and interpretability for real-world applications [17, 18].

Despite progress in emotion-aware chatbot development, few systems are designed to accommodate local languages, idioms, or belief systems prevalent in Ghana. The over-reliance on Western datasets and frameworks limits the cultural appropriateness of current AI tools for mental health. This underscores the need for contextualized, culturally sensitive models to improve adoption and therapeutic impact [19].

2.5. Research Gaps and Justification

While chatbot interventions are well-documented in global literature, gaps remain in their deployment within African mental health systems. Particularly underexplored are generative models that adapt to emotional inputs in culturally meaningful ways. Moreover, few studies combine deep learning-based emotion detection with real-time AI-generated counseling dialogue.

This study addresses these gaps by developing an emotion-aware chatbot tailored for Ghana. It integrates CNN-based emotion classification with GPT-3.5-turbo for context-aware, empathetic dialogue generation. The chatbot is designed to support individuals experiencing anxiety and depression, offering scalable, accessible care in line with Ghana's public health objectives 3.

3. Methodology

This study adopted a structured design methodology to develop and evaluate an AI-powered, emotion-aware chatbot for mental health support in Ghana. The system integrates a deep learning-based emotion classification model with a large language model to generate culturally relevant and emotionally responsive conversations. The methodological framework included four major components: emotion model restructuring, Natural Language Processing (NLP) preprocessing, deep learning training, and system deployment.

3.1. Dataset and Emotion Categorization

The emotion classifier was trained using the International Survey on Emotion Antecedents and Reactions (ISEAR) dataset, which includes over 7,000 manually labeled emotional expressions [19]. Originally labeled with seven categories—joy, fear, anger, sadness, disgust, shame, and guilt—the labels were restructured into five core categories: joy, fear, anger, sadness (merging shame), and disgust (merging guilt), following precedent from affective psychology and emotion classification studies [17].

This reclassification was aimed at improving classification accuracy and simplifying deployment in real-time applications. Figure 1 below shows the flow of the Data preparation, training and best model selection.
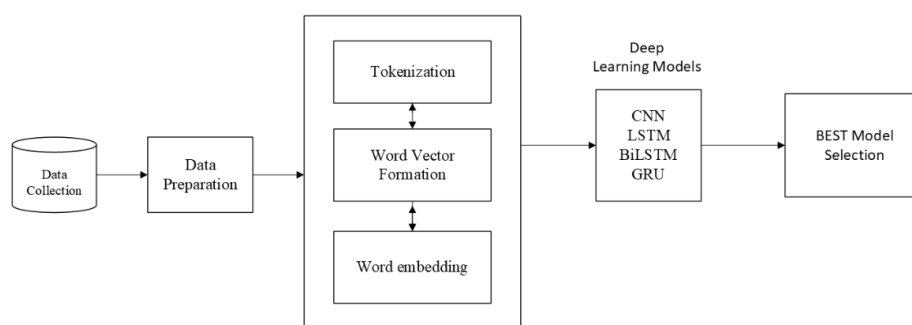

Figure 1. Best model selection.

3.2. Preprocessing and Feature Representation

To prepare the text data for model training, several standard NLP preprocessing steps were applied:
1) Contraction expansion (e.g., "don't" → "do not")
2) Punctuation and stopword removal
3) Text normalization (lowercasing, lemmatization)
4) Tokenization and sequence padding to a fixed length of 300 tokens

Feature representation was achieved using GloVe word embeddings (100-dimensional), which are pretrained on global corpora and proven effective for capturing semantic relationships between words [20].

3.3. Deep Learning Models

Four deep learning models were trained and compared:
1) CNN - Used to extract n-gram-like features from sequences of word embeddings [21].
2) LSTM - Designed to capture long-range dependencies in sequential text [22].

3) BiLSTM - Processes text in both forward and backward directions for richer context [23].

4) GRU - An efficient alternative to LSTM with comparable performance [24].

All models were implemented using Keras and TensorFlow, trained with categorical cross-entropy loss, Adam optimizer, batch size of 500, and early stopping. The CNN model outperformed others, achieving a classification accuracy of 76.4% on the 5-emotion model, with high precision and F1-score.

3.4. Chatbot System Integration

The best-performing model (CNN) was integrated into a conversational pipeline with OpenAI's GPT-3.5-turbo language model. The chatbot interaction sequence as seen in Figure 2 involved:

1) User input is passed through the CNN model.

2) The predicted emotion is used to construct a prompt.

3) GPT-3.5 generates a response tailored to the emotional context.

4) The message is delivered to the user via a web interface.

This hybrid system leverages the precision of a trained classifier and the flexibility of a generative language model to produce empathetic, context-aware dialogue, enhancing user engagement and realism.
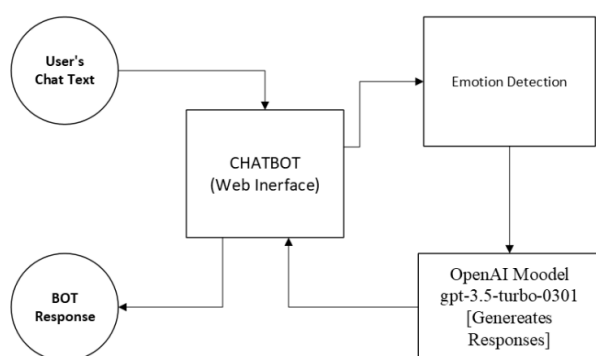

Figure 2. Chatbot Workflow.

3.5. System Deployment and Evaluation

A web-based chatbot interface was developed using Flask (Python backend) and JavaScript frontend, enabling device-agnostic interaction. A pilot study was conducted involving 100 participants from diverse demographics in Ghana. Post-chat evaluations measured:

1) Ease of use

2) Cultural relevance

3) Emotional resonance

4) Likelihood of reuse

5) Willingness to seek professional care

The feedback confirmed the system's practical utility and public health potential.

4. Results

The performance of the emotion classification models and the overall usability of the chatbot system were evaluated in two phases: (1) quantitative evaluation of deep learning models and (2) user-based evaluation of the deployed chatbot prototype. Figure 4 below shows the interface of the Chatbot built.
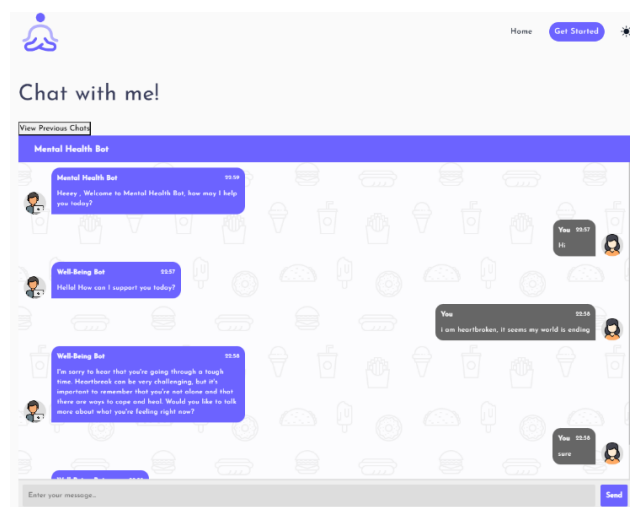

Figure 3. Chatbot's interface.

4.1. Model Evaluation

Four deep learning models—CNN, LSTM, BiLSTM, and GRU—were trained and tested using the 5-emotion classification scheme derived from the ISEAR dataset. The CNN model outperformed all others with an accuracy of 76.4%, precision of 78.3%, recall of 77.6%, and an F1-score of 76.9%. BiLSTM and GRU followed closely but were slightly less consistent, particularly in classifying overlapping emotions like sadness and disgust.

The confusion of the CNN model matrix as shown in Figure 4 below showed high classification of confidence for distinct emotions like joy and fear, with most misclassifications occurring between sadness and disgust. This validated the decision to merge related emotion categories and reduce emotional ambiguity during training.
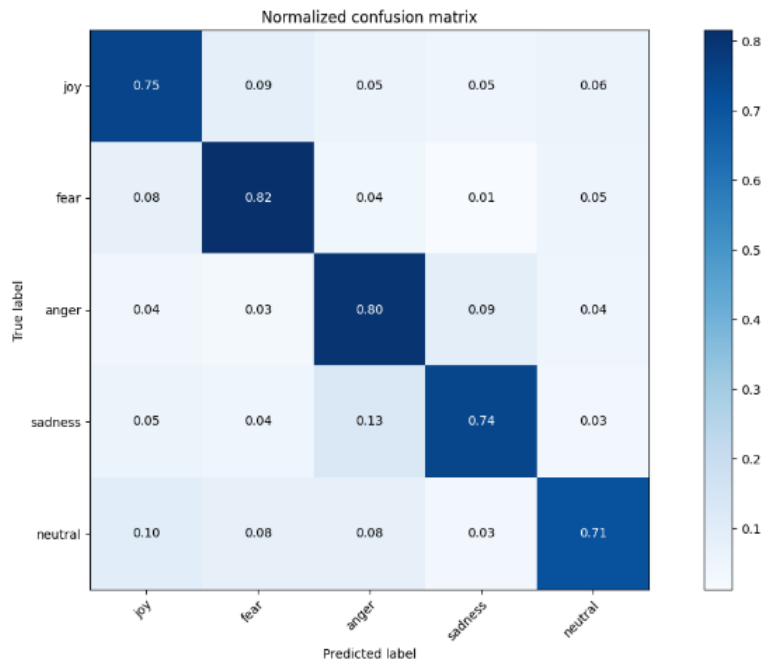
Figure 4. Confusion Metrix.

4.2. Chatbot Usability Evaluation

The integrated chatbot system—comprising the CNN emotion classifier and GPT-3.5 for response generation—was deployed via a web interface and tested by 311 participants in Ghana. Evaluation metrics focused on user experience, cultural appropriateness, and perceived emotional support.

Key user feedback included:

1) Ease of Use: 89% found the system intuitive and accessible. See Figure 6.
2) Cultural Relevance: 81% agreed that the responses reflected Ghanaian social realities and communication styles. Refer to Figure 5.
3) Emotional Support: 78% felt the chatbot provided empathetic and helpful responses. Refer to Figure 8.
4) Help-Seeking Behavior: 66% said the interaction encouraged them to consider seeking professional mental health support. Refer to Figure 9
5) Willingness to Reuse: 84% expressed readiness to engage with the chatbot again in the future. Refer to Figure 7

Users also appreciated the anonymity and 24/7 availability of the system, especially in contrast to in-person therapy sessions, which are difficult to access due to limited personnel and stigma.
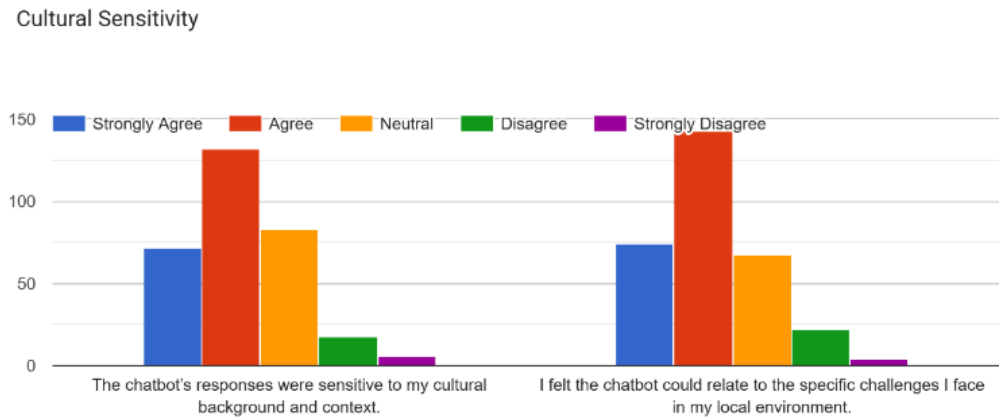

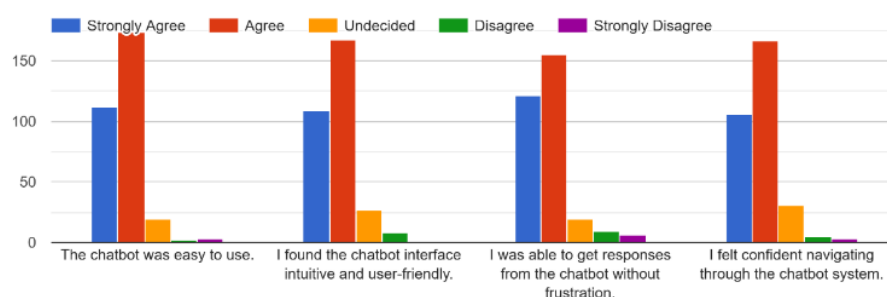*Figure 5. Cultural relevance.*

Ease of Use (adapted from SUS)

Figure 6. Ease of Use.

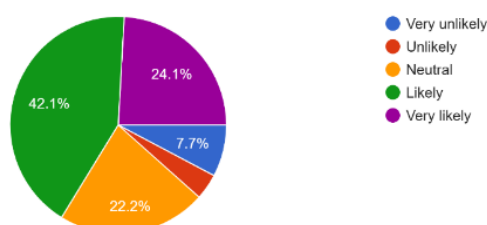How likely are you to use this chatbot again in the future for mental health support?
311 responses

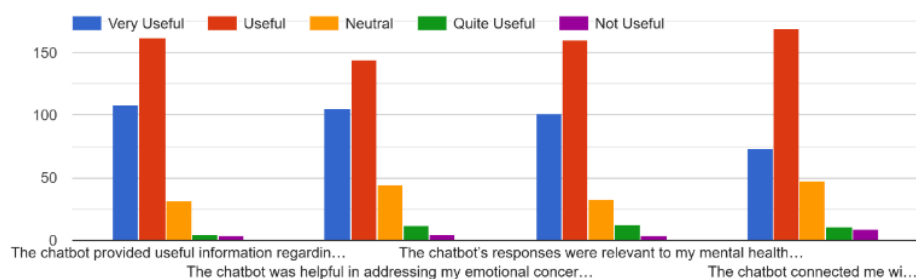*Figure 7. Willingness to Reuse.*

Support and Problem Solving

Figure 8. Emotional Support.

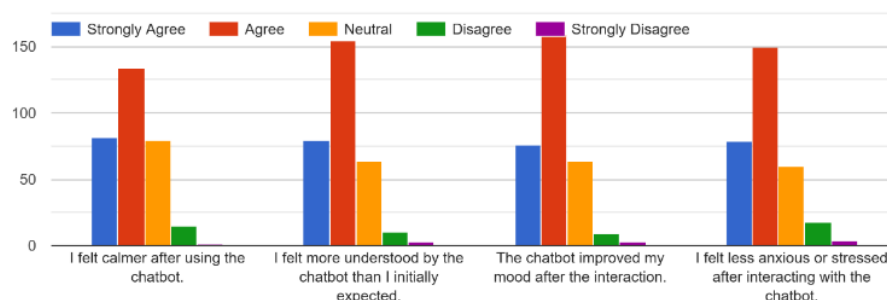To what extent did interacting with the chatbot affect your emotional state?

Figure 9. Ability to connect to psychiatric experts.

5. Discussion

This study demonstrates the feasibility and impact of deploying an emotion-aware AI chatbot to support mental health in low-resource settings like Ghana. By combining a CNN-based emotion classifier with GPT-3.5, the system delivers context-sensitive and culturally relevant responses to users experiencing emotional distress. The model's strong classification performance and positive user feedback validate the effectiveness of this hybrid approach.

User evaluation revealed high satisfaction with the system's usability, cultural appropriateness, and emotional responsiveness. These findings are particularly meaningful in a context where mental health stigma and professional shortages hinder access to care. The chatbot offers a private, always-available alternative to traditional support methods.

However, limitations remain. The system currently supports only English, requires continuous internet access, and lacks crisis intervention features. Addressing these challenges—through language expansion, offline capabilities, and escalation protocols—will be critical for wider deployment and long-term sustainability.

6. Conclusions

This study addressed the critical shortage of accessible mental health care in Ghana, where systemic barriers such as stigma and underfunding leave 98% of the affected individuals without treatment. To bridge this gap, we developed an emotion-aware AI chatbot that combines CNN-based emotion classification (76.4% accuracy) with GPT-3.5-generated responses, offering scalable, culturally adapted support. Key findings from field tests with 311 participants demonstrated high user satisfaction, improved perceived access to support, and potential for scaling as a public health intervention. With about 66% reporting increased willingness to seek professional care, emotion-aware AI chatbot proves to be a promising step toward reducing the treatment gap. Despite the chatbot's 24/7 availability and anonymity in addressing critical barriers in low-resource settings, limitations such as English-only support and internet dependency must be overcome to maximize impact. Future work should explore the integration of local languages (e.g., Twi, Ga) and offline functionality to reach underserved populations. Additionally, more work is needed on developing a strong crisis escalation protocol to connect high-risk users with human providers.

Abbreviations

GPT	Generative Language Model
ISEAR	International Survey on Emotion Antecedents and Reactions
AI	Artificial Intelligence
CNN	Convolutional Neural Network
WHO	World Health Organization
CBT	Cognitive Behavioral Therapy
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Units
NLP	Natural Language Processing

Conflicts of Interest

The authors declare no conflicts of interest.

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