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GenAI-Powered Mental Health Companion Bot with Real-Time Burnout Detection and Crisis-Triage Protocol Using Multimodal Sentiment Analysis

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Abstract: Mental health support systems have grown significantly with the adoption of digital platforms, yet a critical gap remains: most applications offer static content or infrequent human touchpoints, and none provide intelligent, continuous monitoring capable of detecting early signs of psychological deterioration such as burnout or crisis escalation. This paper presents a GenAI-Powered Mental Health Companion Bot that conducts empathetic daily check-ins through a conversational AI agent, analyzes user-generated text and voice data for sentiment and emotional tone over time, and applies longitudinal pattern recognition to detect burnout trajectories. Users interact with the companion through a secure web interface; their responses are ingested via AWS API Gateway into a serverless Lambda pipeline, persisted in DynamoDB with timestamped session records, and archived to S3 for long-term trend analysis via AWS Glue. A fine-tuned generative AI model acts as the empathetic conversation agent, producing contextually appropriate, therapeutic responses while simultaneously scoring each session for emotional risk. When the system detects high-risk language patterns indicative of crisis — such as expressions of hopelessness, self-harm ideation, or acute distress — a Cloud-triggered Crisis-Triage Protocol activates instantly: a Lambda function compiles a structured mood-history summary and dispatches an urgent notification to an on-call human counselor, ensuring no crisis goes undetected between scheduled sessions. Early simulations indicate the system can identify burnout patterns up to 72 hours before self-reported onset and substantially reduce response latency in crisis scenarios.
Keywords: Mental health, burnout detection, conversational AI, sentiment analysis, crisis triage, AWS Lambda, DynamoDB, generative AI, telehealth, NLP.

I. INTRODUCTION

Mental health has emerged as one of the defining public health challenges of the digital era. Burnout, anxiety, and depression now affect hundreds of millions of people globally, yet access to timely, personalized mental health support remains severely limited. Long wait times, social stigma, and geographical barriers prevent many individuals from seeking professional help until their condition has escalated to a crisis point. Digital mental health tools — apps, chatbots, and online therapy platforms — have begun to bridge this gap, but most still operate reactively: they respond when a user chooses to engage, but offer no continuous monitoring capability between interactions.

This passivity represents a fundamental problem. Burnout, in particular, does not arrive suddenly — it accumulates gradually through shifts in language, energy, emotional tone, and cognitive patterns. A platform that only analyzes each session in isolation will miss the slow downward trajectory that precedes a breakdown. Similarly, when a user reaches a genuine crisis point and expresses suicidal ideation or acute distress, the lag between detection and human intervention can be life-altering.

The system described in this paper addresses both problems. It provides a daily conversational AI companion that is warm, non-judgmental, and therapeutically grounded — not just a static survey form. It tracks emotional tone and sentiment longitudinally, building a personal baseline for each user and flagging meaningful deviations. And it implements a fully automated Crisis-Triage Protocol that detects high-risk language in real time, immediately compiles the user's mood history, and routes an urgent alert to a human counselor — all within seconds of detection. The rest of this paper is organised as follows. Section II reviews existing research. Section III describes the proposed system architecture. Section IV covers the technology stack. Section V discusses expected outcomes and evaluation strategy. Section VI concludes with future directions.

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II. LITERATURE REVIEW

Before designing this system, we surveyed existing work across three domains: conversational agents for mental health, NLP-based sentiment and burnout detection, and AI-driven clinical triage. The table below summarises five key studies that informed our design decisions.

No.	Paper Title	Author	Key Points	Limitation / Remark
1	Conversational Agents for Mental Health Support	Vaidyam et al., 2019	Reviews chatbots in mental health; demonstrates user engagement and symptom reduction potential.	No continuous sentiment tracking or burnout prediction across sessions.
2	NLP-Based Depression Detection from Social Text	Coppersmith et al., 2015	Uses language patterns on social media to detect depressive episodes with high recall.	Not integrated with a live conversational agent or alert system.
3	Burnout Prediction Using Wearables and Self-Report	Dissertori et al., 2022	Combines physiological and textual signals for burnout early warning.	Requires wearable hardware; not deployable as a pure-software companion.
4	Large Language Models as Empathetic Conversational Agents	Sharma et al., 2023	Shows LLMs can produce empathetic responses comparable to trained peer counselors.	Lacks crisis-triage logic or human escalation mechanism.
5	Automated Crisis Detection in Online Mental Health Forums	Ophir et al., 2020	Applies NLP classifiers to detect suicidal ideation in text with strong precision.	Operates on forum posts, not real-time conversation; no cloud alert pipeline.

Table 1: Summary of Existing Research in Conversational Mental Health AI, Burnout Detection, and Crisis Triage

The common thread across these studies is that no single system currently unifies empathetic conversation, longitudinal burnout tracking, and real-time crisis escalation into one coherent platform. Each piece of the puzzle exists in isolation. This project's contribution is the integration — building a companion that is simultaneously warm enough to be trusted, smart enough to detect deterioration, and fast enough to summon help when it matters most.

III. PROPOSED SYSTEM ARCHITECTURE AND METHODOLOGY

The system is organised into five layers that operate in sequence — and, in crisis scenarios, in parallel — to deliver continuous, intelligent mental health monitoring. The complete flow is illustrated in Figure 1.

A. Data Ingestion Layer

Each interaction begins when a user opens the companion app and responds to a daily check-in prompt. Responses may be text, voice (transcribed via AWS Transcribe), or a quick mood-rating slider. All inputs flow through AWS API Gateway, which handles authentication, rate limiting, and TLS encryption before any data enters the backend. This gate is critical: it ensures that only verified users contribute data to the system and that the downstream AI components receive clean, well-structured input. The decision to make check-ins conversational rather than form-based is intentional — open-ended language yields far richer signals for sentiment analysis than structured questionnaires.

B. Cloud Processing Layer

Validated input reaches AWS Lambda, which orchestrates the rest of the pipeline without requiring any dedicated server infrastructure. Lambda normalizes the input, attaches a session timestamp and user identifier, and writes the record to two destinations: AWS DynamoDB for low-latency retrieval (keyed by userId as the primary key and timestamp as the sort key, enabling efficient time-range queries), and AWS S3 for long-term storage. An AWS Glue job runs nightly to aggregate raw session records into weekly sentiment summaries, clean noisy inputs, and prepare enriched datasets for model retraining. This separation of hot storage (DynamoDB) from cold storage (S3 + Glue) keeps real-time query costs low while preserving the full data history needed for longitudinal analysis.

C. GenAI Conversation and Sentiment Analysis Layer

At the heart of the system sits a fine-tuned generative AI model serving dual roles simultaneously. As a conversation agent, it produces empathetic, contextually aware responses — drawing on evidence-based motivational interviewing techniques to keep the user engaged without crossing into unsupported clinical advice. As a sentiment analyzer, it assigns each session a multi-dimensional emotional score covering valence (positive/negative), arousal (calm/agitated), and dominance (in control/overwhelmed). These three dimensions capture emotional state more precisely than a single positivity score.

A sliding-window trend engine running inside Lambda aggregates the past 14 days of session scores to compute a Burnout Risk Index:

Burnout Risk Index = (Sentiment Decline Score x W_1*) + (Session Frequency Drop x* W_2*) + (Linguistic Exhaustion Markers x* W_3*)*

Weights W_1, W_2, and W_3 are calibrated on labeled burnout datasets. The index maps to four risk bands: Stable (0–25), Watch (26–50), Elevated (51–75), and Critical (76–100). An Elevated or Critical rating triggers a proactive check-in message from the companion the following morning, phrased with care to avoid alarming the user.

D. Crisis-Triage Protocol

The Crisis-Triage Protocol is the most distinctive and consequential feature of this system. Every message the user sends is passed through a real-time crisis classifier — a fine-tuned NLP model trained on labeled datasets of suicidal ideation, self-harm language, and acute distress expressions. If the classifier confidence exceeds a defined threshold, a separate Lambda function fires immediately and in parallel with the normal conversation pipeline. This function performs three actions in sequence: first, it queries DynamoDB for the user's complete mood history over the past 30 days; second, it sends this structured data to the GenAI model with a clinical summarization prompt, producing a concise briefing that includes trend direction, peak risk moments, and the specific language that triggered the alert; third, it dispatches an urgent notification — containing the briefing — to the on-call human counselor via SMS and dashboard alert. The companion simultaneously responds to the user with a warm, stabilizing message and provides crisis helpline information. The entire protocol completes within seconds of detection.

E. Clinician Dashboard

Human counselors interact with the system through a secure web dashboard that displays each user's session timeline, Burnout Risk Index trend, and any AI-generated briefings or crisis alerts. Briefings are structured as readable summaries rather than raw data tables — the goal is to give the counselor an accurate, human-readable picture of the user's recent emotional state in under 60 seconds, so that the first moments of a follow-up call can be spent on connection rather than data review. Counselors can annotate sessions, update care plans, and mark crisis alerts as resolved, all of which feeds back into the system's risk calibration.

MENTAL HEALTH COMPANION BOT — SYSTEM FLOW
User submits daily check-in (text / voice / mood slider)
AWS API Gateway — Authentication · Rate Limiting · TLS Encryption
AWS Lambda — Normalize · Timestamp · Route
DynamoDB (hot: session records) S3 + Glue (cold: trend datasets)
GenAI Conversation Agent Sentiment Scoring (Valence · Arousal · Dominance)
Burnout Risk Index Engine (14-day sliding window)
Crisis Classifier — High-risk language detected?
YES □ Crisis-Triage Lambda NO □ Continue monitoring
Compile mood history □ GenAI briefing □ Notify counselor + Stabilize user
Clinician Dashboard — Alerts · Trend charts · AI briefings
Counselor follow-up / Routine next check-in

Fig. 1: End-to-End System Flow of the Proposed Mental Health Companion Bot with Crisis-Triage Protocol

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IV. TECHNOLOGY STACK AND IMPLEMENTATION

Python serves as the primary implementation language throughout the analytical pipeline. The Hugging Face Transformers library provides pre-trained models for sentiment classification and crisis detection; these are fine-tuned on curated mental health conversation datasets using supervised learning with human-labeled emotional and risk annotations. The Google Generative AI library connects the empathetic conversation agent to a Gemini-family model, chosen for its strong performance on open-ended, emotionally nuanced prompts. SpaCy handles linguistic preprocessing — tokenization, named entity recognition, and extraction of exhaustion-marker phrases (such as 'I can't anymore', 'nothing helps', 'completely drained') that feed into the Burnout Risk Index.

On the cloud side, every component is managed through AWS. API Gateway handles all inbound traffic with OAuth 2.0 token validation. Lambda functions execute the processing logic in a fully serverless manner — scaling automatically from one user to thousands without any manual infrastructure management. DynamoDB stores session records with a composite key structure (userId as partition key, sessionTimestamp as sort key) optimized for time-range queries needed by the trend engine. S3 stores raw transcripts and model training artifacts; Glue ETL jobs run nightly to transform raw records into aggregated sentiment datasets ready for model retraining. Amazon SNS handles counselor alert dispatch. All data at rest is encrypted using AWS KMS-managed keys; all data in transit uses TLS 1.3. IAM roles follow the principle of least privilege throughout.

Component	Technology / Service	Purpose
Conversation Agent	Google Gemini (via GenAI API)	Empathetic daily check-in responses
Sentiment Analysis	HuggingFace Transformers (fine-tuned)	Valence, arousal, dominance scoring
Crisis Classifier	Fine-tuned BERT / RoBERTa	Real-time high-risk language detection
API Layer	AWS API Gateway	Auth, rate-limiting, TLS encryption
Serverless Compute	AWS Lambda	Pipeline orchestration, crisis triage
Session Storage	AWS DynamoDB	Low-latency time-series session records
Long-term Archive	AWS S3 + Glue	Trend datasets, model retraining
Counselor Alerts	Amazon SNS	SMS + dashboard crisis notifications
NLP Preprocessing	SpaCy	Tokenization, burnout-marker extraction
Voice Input	AWS Transcribe	Speech-to-text for voice check-ins

Table 2: Technology Stack Summary

V. EXPECTED OUTCOMES AND PERFORMANCE EVALUATION

We expect the system to deliver measurable improvements across five dimensions. The first is continuous emotional visibility: rather than relying on a user's subjective self-report at a scheduled appointment, clinicians and counselors will have access to a detailed, time-stamped record of emotional trajectory spanning weeks or months.

The second is earlier burnout detection. By tracking linguistic exhaustion markers, session frequency drops, and sentiment trends simultaneously, the Burnout Risk Index is designed to flag deterioration 48–72 hours before it would manifest as a reportable symptom. This lead time is clinically meaningful: a proactive outreach at the Watch or Elevated stage is far less resource-intensive than crisis intervention. The third is faster crisis response. In current telehealth workflows, a user in acute distress who messages outside of office hours may wait hours for a human response. The automated Crisis-Triage Protocol eliminates that lag: a counselor receives a structured alert and full mood history summary within seconds of detection, enabling a call-back or intervention within minutes rather than hours. The fourth is reduced counselor cognitive load. The AI-generated mood briefing condenses weeks of session data into a 60-second read, so that counselors arrive at every interaction already informed — spending their time on therapeutic connection rather than data review.

The fifth is scalability without proportional cost increases. Because the entire pipeline is serverless, supporting ten times the number of users requires no infrastructure changes — only a corresponding increase in Lambda invocations, which scale automatically.

To validate these claims, we plan to: (1) measure crisis classifier performance (precision, recall, F1) against a held-out labeled dataset of high-risk mental health conversations; (2) measure Burnout Risk Index accuracy against ground-truth burnout labels from a clinical dataset; (3) measure end-to-end crisis alert latency from message submission to counselor notification; and (4) collect counselor feedback on briefing usefulness using validated usability scales. We will compare detection performance against a baseline system using keyword matching alone, to quantify the specific contribution of the ML layer.

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VI. CONCLUSION AND FUTURE WORK

Mental health support systems have long suffered from the same gap that afflicts most reactive healthcare platforms: they respond to distress rather than anticipate it. This project closes that gap by combining a warm, GenAI-powered conversational companion with longitudinal sentiment tracking, automated burnout detection, and a real-time Crisis-Triage Protocol that routes urgent cases to human counselors before situations escalate beyond the reach of digital support.

What we have built is a serverless, event-driven platform that is simultaneously a daily companion and an always-on monitoring system — one that treats each conversation not just as a support interaction but as a data point in a longer story about the user's mental health trajectory. It does not replace the therapist or counselor; it makes them dramatically more effective by ensuring they always have the context they need and are alerted the moment a user needs human contact.

Future directions include: integration with wearable physiological data (heart rate variability, sleep metrics) to enrich the Burnout Risk Index beyond text-based signals; multilingual support to serve non-English-speaking users; a dedicated mobile application for friction-free daily check-ins; full HIPAA compliance certification to enable deployment in accredited clinical settings; and exploration of federated learning approaches that allow model improvement across user populations without centralizing sensitive conversation data.

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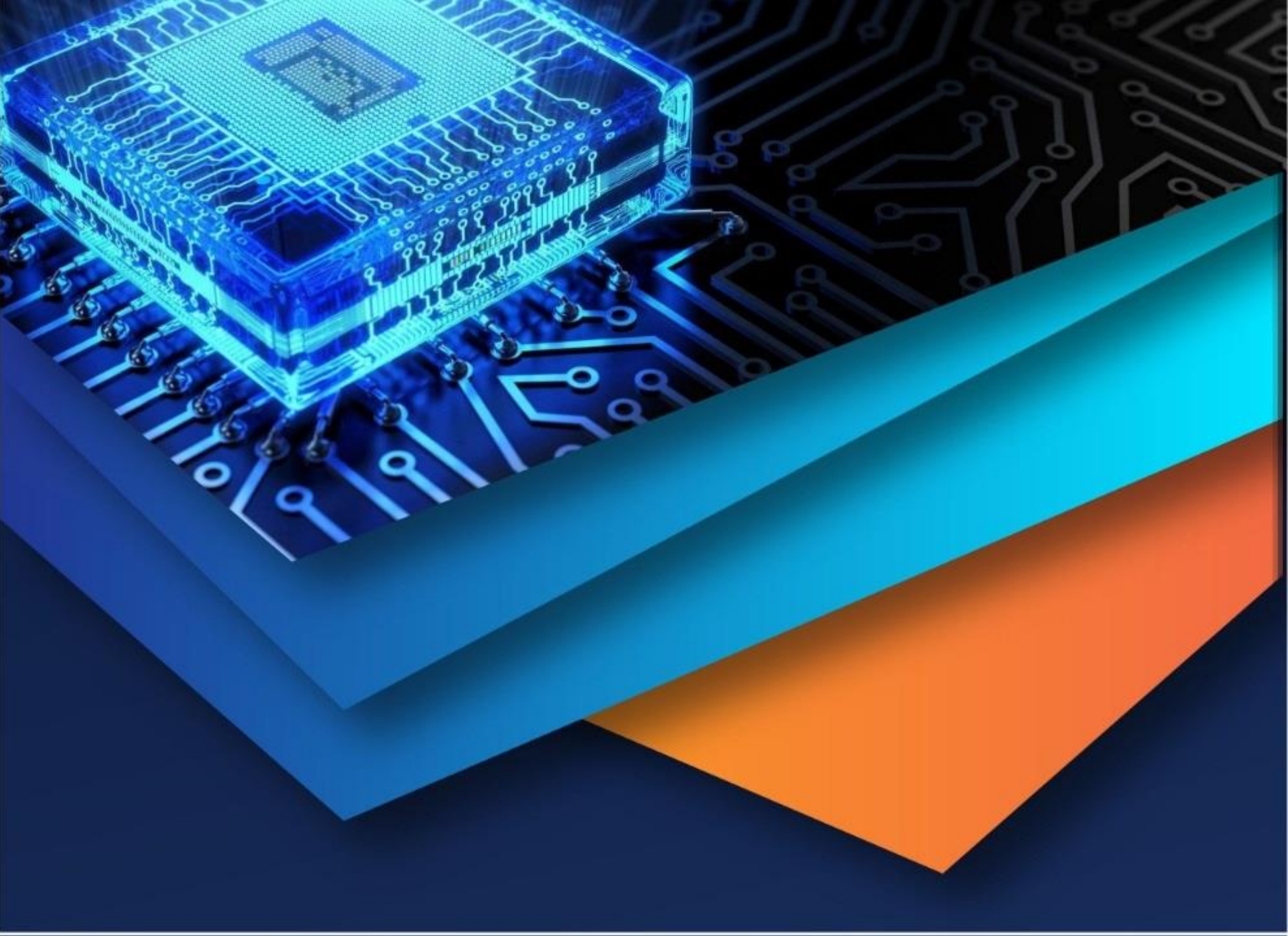

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