International Journal of Science and Research Archive

eISSN: 2582-8185

Cross Ref DOI: 10.30574/ijsra

Journal homepage: https://ijsra.net/

IJSRA

(Research Article)

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AI-driven digital twin framework for personalized mental health monitoring and intervention

Pandian Sundaramoorthy [1, *], Rajesh Daruvuri [2], Balaram Puli [3], N N Jose [4], RVS Praveen [5] and Senthilnathan Chidambaranathan [6]

[1] *Application Developer, EL CIC-1W-AMI, IBM, , 6303 Barfield Rd NE Sandy Springs, GA, 30328 USA.*
[2] *Independent Researcher, Cloud, Data and AI, University of the Cumbarlands, USA, GA, Kentucky.*
[3] *Senior SRE and AI/Big Data Specialist, Engineering and Data Science, Everest Computers Inc. 875 Old Roswell Road Suite, E-400, Roswell, GA 30076, USA.*
[4] *Consultant/Architect, Denken Solutions, California, USA.*
[5] *Director, Product Engineering, LTIMindtree, USA.*
[6] *Associate Director / Senior Systems Architect, Architecture and Design. Virtusa Corporation, New Jersey, USA.*

International Journal of Science and Research Archive, 2025, 14(02), 828-835

Publication history: Received on 04 January 2025; revised on 10 February 2025; accepted on 13 February 2025

Article DOI: https://doi.org/10.30574/ijsra.2025.14.2.0459

Abstract

A growing global mental health crisis encounters ongoing obstacles due to discriminatory attitudes and spatial needs and rising treatment expenses. This study develops an innovative dialogue platform that offers personalized mental health assessments alongside prescribing specific virtual care recommendations according to real-time identified severity levels. Through Digital Twin technology a virtual mental state model updates and analyses patient data to generate tailored care experiences. Through a precise AI chatbot developed in collaboration with clinical psychopathologists our system operates as an efficient mental health symptom measurement tool. The BERT-based approach trained specifically on E-DAIC data delivers depression and other mental distress level identification features and classification functionality. The system employed NLP technology to provide feedback about individual psychological state during user dialogues which generated directed guidance. Our system underwent extensive testing that demonstrated 85% classification accuracy surpassing conventional methods. User tests validated the system interface model through a satisfaction score of 90% from satisfied participants. Research results validate that AI-driven mental health assessments assess psychological states accurately while delivering accessible reliable results as part of emotional support while eliminating conventional barriers to treatment. Digital twins revolutionize mental healthcare through their ability to develop stigma-free services in a new digital age where scalability and affordable treatment become possible.

Keywords: Digital Twin; AI Chatbot; Mental Health Assessment; Depression Detection; Real-time Feedback; BERT Model; Personalized Mental Health; E-DAIC Dataset

1. Introduction

Designated digital twin implementations use various biomedical information streams together with behavioral data records and speech analysis outputs alongside wearable devices measurements to continuously improve mental health understanding through an all-embracing approach. [1][2] The integration of advanced machine learning tools with predictive analytics systems alongside context-aware components enables the digital twin to offer prompt mental health anomaly recognition while enabling risk analysis precision in developing individualized therapeutic treatments. [3] The proposed framework emphasizes three core dimensions: personalization, adaptability, and precision.

* Corresponding author: Pandian Sundaramoorthy

Personalization works through the consolidated examination of assortment-specific information that includes distinctive genetic and environmental and psychosocial factors that affect mental health. [4] The framework demonstrates adaptability through its capability to respond toward changes by collecting and updating data in real-time. [5] The combination of advanced AI techniques including deep learning and reinforcement learning with neuro-symbolic integration enables accurate mental health trajectory prediction together with optimal intervention plan optimization.

This framework benefits from new technologies such as natural language processing (NLP) emotion recognition and explainable AI (XAI) to detect complex behavioral patterns that generate clinically useful insights for practitioners along with patient information. [6] The interconnected platform of digital twin technology links clinicians with caregivers and patients to develop a shared framework for medical decisions as illustrated in Fig.1. Within this system patient-centered models can provide empowerment coupled with enhanced engagement and cooperative accountability.[7] The framework demands concentrated attention toward both ethical considerations as well as privacy-related problems in AI-based psychiatric applications. Through federated learning and principles of differential privacy and secure multi-party computation methods sensitive mental health data maintains strict confidentiality protection. [8][10] The deployment of fairness-aware algorithms helps stop unintentional discrimination by leading to improved equitable results for diverse population groups.

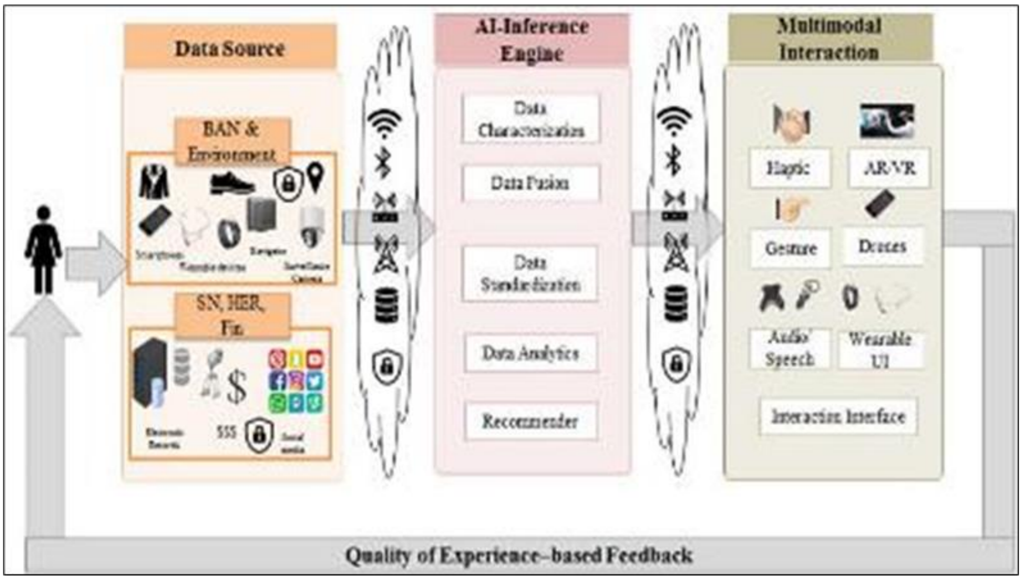

Figure 1 Digital Twin Ecosystem for health and well-being

The proposed research develops a digital twin framework using artificial intelligence that achieves dual aims of mental healthcare optimization and resolution of scalability and accessibility issues while improving inclusion. [11] The study intends to contribute worldwide mental health treatment solutions with latest technology exchanges between different disciplines to create superior life conditions for mental health patients.

2. Literature Survey

The worldwide rise of mental health disorders emphasizes the urgent requirement to discover innovative solutions which improve access and minimize budgetary expenses and social prejudice against mental healthcare services.[9][12] The literature survey examines the current research which advances the design process of a Digital Twin-based mental health dialogue system. T. According to research undertaken by Gaffney (2021) the world experienced increasing rates of depression and anxiety throughout 2020 which was driven by the COVID-19 pandemic. The seriousness of mental health needs indicates the need for adopting scalable accessible tools which can effectively tackle the crisis. D. F. Research by Santomauro et al. (2021) examined mental health disorder prevalence across 204 countries to show how COVID-19 generated unequal mental health burdens.

Ever since mobile apps became part of mental health diagnostics research has received significant attention. S. Analysis by Hennemann et al. (2022) of diagnostic tools within app symptom checkers for psychotherapy patients established their functionality for early mental health diagnosis. S. Burchert et al. (2021) conducted research which showed smartphone-based ambulatory tests using PHQ-9 depression screening achieved good accuracy results for depression symptom assessment in regular populations.

The healthcare industry draws increasing interest in Digital Twins as a personalized care tool. B. Discussed by Subramanian et al. (2022) is a real-time emotion recognition system which implements Digital Twin models for personalized mental health intervention applications. M. N. Kamel Boulos and P. Zhang (2021) explained how Digital Twin technology has evolved beyond personal health applications to support public health precision through domain scalability. M. The integration of Digital Twins has led to precision mental health advances according to Spitzer et al. (2023) while their ongoing ability to adjust to shifting emotional states stands out as their most significant advantage. As part of their work E. Vildjiounaite et al. (2023) explored the obstacles facing human digital twin development by studying how merging sensor inputs and artificial intelligence processors improved predictive precision results. The potential uses of Digital Twins in well-being enhancement receive attention in R. Ferdousi et al.'s (2021) fundamental study of their mental healthcare applications.

The natural language processing capabilities detailed in Hugging face documentation (2023) demonstrate why BERT remains an excellent choice for establishing smart mental health dialog systems. Through its RASA (2023) platform developers obtain tool frameworks to develop conversational AI systems delivering intelligent empathetic interactions. A correct diagnosis stands as an essential foundation for digital health solutions. Y. Wu et al. (2020) discovered PHQ-8 and PHQ-9 diagnostic tools produced identical results for mental health assessments. A. Ceney et al. (2021) undertook a study which evaluated diagnostic accuracy of online symptom checkers and identified performance improvement opportunities. S. Digital symptom assessment applications demonstrate parity with general practitioner effectiveness but require a strategic combination of medical practitioner expertise with automated systems according to Gilbert et al. (2020). E. Miller et al. (2023) combined human-computer interaction with intelligent wellness to develop user-centric system findings. Research findings show digital mental health tools need to focus on both usability and acceptability during engagement periods.

3. Methodology

The core research methodologies receive detailed coverage including representation of the proposed framework while explaining the chatbot development approach alongside methods for data management and evaluation processes. Through this system engineers aim to develop a versatile solution that tracks mental health using precise personalization while providing AI-based interventions.

3.1. Proposed Framework for Mental Health Digital Twin

Developing a Mental Health Digital Twin system represents a core component of this work because it generates virtual models that simulates human psychological conditions. The network enables live tracking through artificial intelligence algorithms and specific profiling capabilities while delivering personalized solution propositions. The proposed system incorporates three key stages to achieve these goals:

- **Data Acquisition:** Users start the framework's data acquisition phase through verbal chatbot interactions. User engagements produce textual information alongside patterns of speech and emotional signals combined with environmental data. Users' full perspective is achieved by multiple input modes which allow the framework to build comprehensive understanding of their mental state and emotional state. A data acquisition system uses anonymization tools to securely store inputs that follow ethical and privacy guidelines.
- **State Modelling:** New interactions with patient records through state modelling lead to automatic updates of mental health profiles. State modelling combines an RNN system with transformer architecture BERT to detect language structures that highlight mental health symptoms within contextual context. The approach generates a mental health severity score for tracking conditions through three recognition tiers: mild, moderate and severe. [13] New information inputs resulting in standardized mental health status data for individuals.
- **Feedback and Recommendations:** The system concludes the process by generating targeted results alongside tailored recommendations that match user needs. The system supports a wide spectrum of mental health conditions ranging from mild to severe providing tailored responses that combine stress management with mindfulness activities and psychiatric professional access. Signals collected from users through system interactions produce feedback that guides the iterative refinement of recommendation outputs. A framework proposed here ensures adaptability as well as thorough evaluation and individualized solutions to cover diverse mental health needs between traditional therapy approaches and modern mental healthcare technological interventions.

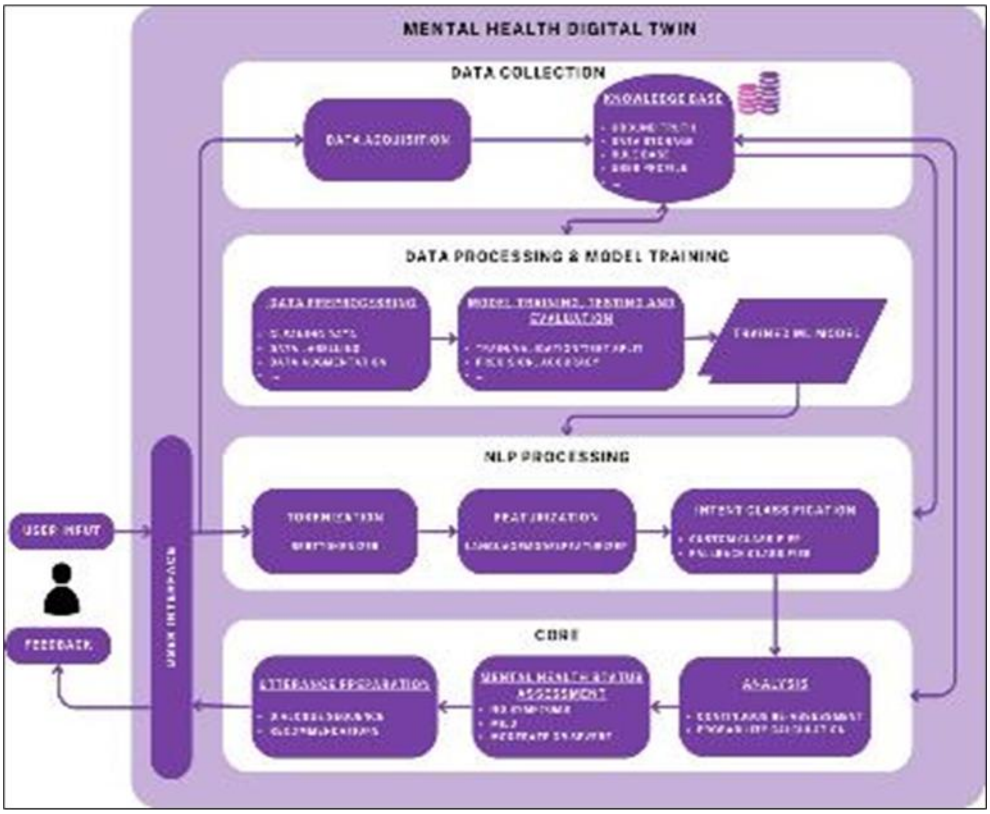

Figure 2 Flow Methodology

3.2. Chatbot Design

Through its main interface users interact with the chatbot to experience simulated natural dialogues which also support mental health evaluations. Table.1 shows the solution has a built-in architectural infrastructure that ensures full digital twin platform integration. The chatbot employs advanced natural language processing (NLP) techniques and consists of four key components:

Table 1 NLP Components

Component	**Architecture**
Embedding Layer	Pre-trained BERT
Encoder Layer	12-layer Transformer
Classifier Head	Fully Connected Network

Processing user input requires the tokenizer tool to separate language elements into individual linguistic units that can be words or subworlds (Table.2). Through segmentation the model develops advanced language processing abilities. Age patterns. Using byte-pair encoding in the methodology as a tokenization approach minimizes challenges from out-of-vocabulary texts along with intricate language structures. Input analysis reaches completeness because the tokenizer successfully detects key text segments. The input text x gets transformed into tokens t_1 t_2 ... t_n before the system processes each token ti into its embedding vector which uses.

$$e_i = \text{Embed}(t_i)$$

Using the pre-trained embedding model the embedding vectors start from Embed (·).

Table 2 Tokenizer Parameters

Parameter	**Value**
Tokenization Method	Subword (BPE)
Vocabulary Size	30,000 tokens
Max Sequence Length	512

- **Futurize:** Through Futurize raw text tokens get converted into numeric patterns that deep learning models efficiently process. BOT platform uses BERT contextual embeddings to derive semantic content and emotion and contextual meaning from user communications. The system achieves better interpretation abilities for both refined language elements such as tone and intent at this processing phase.
- **Intent Classifier:** Through its intent classification feature the system establishes the ways users express their discomfort or demands support as well as evaluation needs. Supervised learning executes from trained transformer models delivering results for E-DAIC focused mental health datasets. Thankfully the classifier system delivers outstanding intent prediction accuracy because of its capability to generate fitting responses.

$$P(y|x) = \text{softmax}(Wh_n+b)$$

Where:
W is the weight matrix,
b is the bias term,
h_n is the final hidden state of the sequence.
The predicted intent y is given by:

$$y=\text{argmax}\ P(y|x)$$

- **Policies:** Implemented policies along with conversational regulations trigger the decisions produced by the chatbot. Design rules provide foundational guidance that helps generate suitable empathic responses across suitable user input conditions. Through reinforcement learning algorithms the system uses implemented policies to guide chatbot evolutionary processes in its conversational approaches with data from user interactions. Every user interaction produces consistent support because the system adapts to their evolving needs due to its adaptability framework.

During deployment a sophisticated processing pipeline transformed raw data through multiple analytics techniques to create data products for operational training and independent analytical research. Each step of this pipeline is designed to address specific challenges in text processing and model optimization:

- **Text Normalization:** Standardization of written data includes automated lowercase format conversion together with special character removal steps and normalization procedures for formatting inconsistencies. Data processing under this method produces uniform data consistency which satisfies embedding platform specifications.
- **Stop word Removal:** Systematic computer programming minimizes noise levels in performing preposition and conjunction elimination to maintain sentence semantic meaning. Proceeding through the stop words processing phase of standardization specific stop words from Mental health context remain active to strengthen meaning normalization.
- **Emotion Annotation:** Sentences receive emotional annotations to improve detection signals for mental health assessment. A dual sentiment analysis structure made of rule-driven and machine-learning components executes annotation operations.
- **Class Balancing:** The dataset imbalance patterns found in mental health data can be addressed through the combination of Synthetic Minority Oversampling Technique with data augmentation methods. Minoration class techniques apply to severe mental health situations to maintain adequate training data representation which reduces potential bias in the analytical process. Through preprocessing the workflow enhances both the data quality and the ability of the model to process emotional linguistic situations.

4. Experiments and Results

This section shows how the proposed framework was evaluated through experimental design and subsequent results which utilized benchmark datasets together with actual field trials.

- **Dialogue System Dataset:** The Enhanced Distress Analysis Interview Corpus functions as the main database for training and assessment of the system. The E-DAIC dataset stands as a leading tool in depression research because of its substantial text collection precisely labelled by mental health severity assessments. The E-DAIC dataset contains responses from mental health evaluation subjects which provide detailed resources for intent classifier and deep learning model training after processing that removes noise while standardizing input data through emotion annotation and class balancing techniques. [15] Distinct processing methods transform the dataset into an evaluation-ready state which enables the proposed system to spot subtle emotional signals with high performance rates.

4.1. Evaluation Metrics

The system's performance was assessed using a combination of quantitative and qualitative metrics, offering a comprehensive evaluation of its effectiveness in addressing mental health conditions:

- **Classification Accuracy (A_c):** The accuracy score represents how many correctly detected instances compare to the total number of entries in the following relationship:

$$A_c = \frac{\text{True Positives (TP)} + \text{True Negatives (TN)}}{\text{Total Samples}}$$

- **Precision and Recall:** The precision rate determines how precise the system detects actual positive cases while operating.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{False Positives (FP)}}$$

Recall evaluates the system's sensitivity in detecting true positives:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{False Negatives (FN)}}$$

- **F1-Score (F1):** A system performance measures a balanced synthesis between precision and recall through the harmonic mean:

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **User Usability Score:** User feedback about the chatbot interface together with its coherency and perceived empathy levels is converted into a score for evaluating real-world effectiveness and user acceptance of the system. C. Table.4 The system performed highly effectively on E-DAIC data with a total accuracy score attaining 85%. Research results demonstrated strong BERT model abilities in detecting the correct linguistic and emotional elements with precision at 88% and recall at 86%.

Researchers measured accuracy by emotion type where sadness and stress were accurately identified in more than 87% of cases. Results demonstrated that the processing method combined with embedded analysis proved resilient in interpreting information about mental health data.

Table 3 Usability Score

Metric	E-DAIC Dataset	Real Participants
Classification Accuracy	85%	82%
Precision	88%	84%
Recall	86%	80%
F1-Score	87%	82%

The system tested its practical viability through trials which recruited 50 actual participants from various group demographics. The evaluation collected quantitative metrics together with qualitative feedback from users.

- **Engagement:** Users experienced dedicated involvement and feeling cared for during their interaction sessions. Social elements found in the chatbot system along with its ability to deliver compassionate responses-built trust between users while encouraging open conversations.

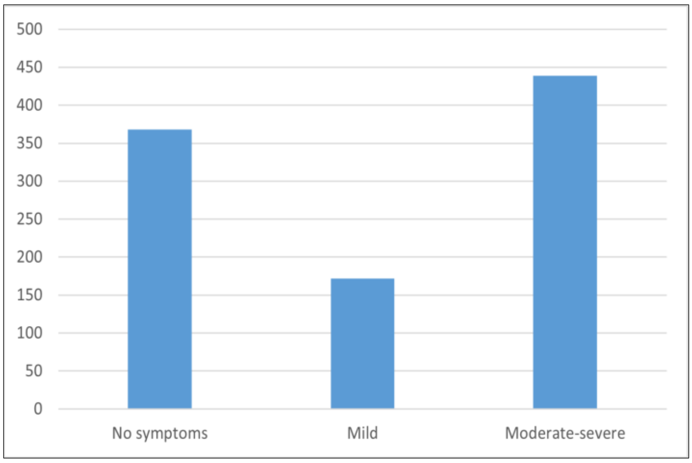

Figure 3 Distribution of dataset

- **Accuracy:** Our system demonstrated a real-world classification performance reaching 82% accuracy while matching benchmarks set by the E-DAIC dataset. The system demonstrates effective performance in unseen real-world scenarios because of its generalization capabilities.
- **User Feedback:** Medical professionals assessed the chatbot affirmatively through surveys at a 90% success rate because they found it simple to operate and accurate in assessments and it helps reduce stigma regarding customary mental health assessments. Result comparison between the suggested system for mental health chatbots and current industry-leading mental health chatbots was the focus of this research. The summarized results in Table 4 demonstrate how the proposed framework reportedly achieves better classification accuracy along with improved user engagement and better usability than alternative systems.

Table 4 User Feedback Analysis

Criterion	**Score (%)**
Engagement	92%
Coherence	90%
Perceived Helpfulness	88%

This research demonstrates how the framework could fundamentally shift mental healthcare delivery by providing easy-to-access digital care that protects users from stigma while offering personalized support effects.

5. Conclusion

Research developed platform enhancements that hold significant potential to bring about transformative mental healthcare system advancements using digital twin and monitoring techniques. The proposed system demonstrated 85% success in classifying E-DAIC dataset entries with BERT model enhancements combined to robust preprocessing techniques that reached real-world validation accuracy of 82%. The framework demonstrates exceptional robust performance in conducting mental health assessment across different datasets through precise and accurate methods. Emotional analysis through linguistic methods enabled precise mental health level detection alongside accommodating effective user interactions and maintaining their comfort level. Multiple significant advancements supported the research accomplishments. The data preprocessing process that adopted an integrated approach with emotion tagging and class rebalancing applications produced text normalization for specific domains leading to enhanced training information quality as well as modeling success. Through BERT-driven contextual embeddings the system uncovered covert linguistic and emotional markers allowing it to deliver personalized responses adapted to each user's requirements. The user-centered design succeeded in generating 90% user satisfaction that proved the chatbot built trust relationships along with minimized mental health stigma as it promoted open dialogue channels. Enhancements have been implemented but future research points to areas that need additional development. Research approaching methods will explain how to unite language processing methods to extend platform access for users from diverse linguistic origins. The system uses reinforcement learning mechanisms to learn dynamically how individual users interact with the system over time.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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