



# A Hybrid Chatbot System For Alzheimer Disease Screening And Treatment Recommendation Using Clinical Nlp

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**Abstract:** Alzheimer's Disease (AD) is an ever-growing neurodegenerative condition seriously debilitating cognitive functions and posing the requirement of early diagnosis and treatment. Use of AI-based chatbots integrating Natural Language Processing (NLP) and Machine Learning (ML) has shown to be effective in screening cognitive disorders in the last few years. This survey discusses the existing hybrid chatbot architectures specifically aimed at screening and recommending treatment of Alzheimer's disease. The baseline paper taken into consideration, "A Hybrid Transformer-Based Model for Alzheimer's Disease Prediction from Conversational Data" (Elsevier, 2025), harmoniously combines conversational AI and understanding of clinical language to provide precise diagnosis. We discuss comparative studies published in recent journals of Q1 and the limitations of existing models on computational complexity and non-personalization. We finally introduce pragmatic solutions with regards to student-level work with resource constraints. The objective is to introduce an updated, efficient, and cost-effective chatbot architecture yielding maximum diagnostic accuracy and clinical usability.

**Index Terms - Alzheimer's Disease, Clinical NLP, Hybrid Chatbot, Conversational AI, Transformer Models, Cognitive Screening**

## I. INTRODUCTION

Alzheimer's Disease (AD) is the leading cause of dementia and has an estimated 55 million affected worldwide. Diagnosis of the initial stage of AD is vital to halt the progress of the disease and to enhance the quality of life. The traditional screening is largely accompanied by the visits to clinics, neuropsychological testing, and the services of professionals, which are time-consuming and inaccessible to the majority. With the technological advancement of Artificial Intelligence (AI) and the enhanced condition of Natural Language Processing (NLP), chatbots are fast becoming effective tools for conducting the assessment of cognitive health. These bots mimic actual dialogue and are able to pick up on subtle impairments in language that are typical of AD. Hybrid models that fuse transformer-based NLP (i.e., BERT, GPT, and LLMs) and clinical reasoning frameworks are extremely promising diagnostic tools. This survey discusses existing hybrids chatbots for Alzheimer diagnosis and recommendation, with an emphasis on models that employ clinical NLP methodologies. We are basing our assessment on the recent paper "A Hybrid Transformer-Based Model for Alzheimer Disease Prediction from Conversational Data" and contrasting it with related frameworks. The main intent of the work is to fill the void bridging the divide between the existing research and proposing an easier to implement but more precise and resource-wiser model appropriate for real-time use. We'd rather help student investigators and health developers design smarter Alzheimer's screening devices pragmatic enough to function well with sparse computational and budget resources.

## II. LITERATURE SURVEY

The research, "**A Hybrid Transformer-Based Model for Alzheimer's Disease Prediction from Conversational Data**," presented a hybrid model that cognitive decline in its early stage by analyzing patient speech [1]. Employing deep contextual embeddings of BERT along with transformer encoders for extracting syntactic and semantic properties of Alzheimer-induced linguistic degradation, its ability in dealing with unstructured conversational text enables real-time diagnosis, dramatically improving in detection of subtle signs in the earlier stage. It provides equal emphasis on interpretability and real-world usability in both clinical and non-clinical settings. The article "**Multimodal Deep Learning Models for Detecting Dementia From Speech and Transcripts**" presents a complete system that combines textual and auditory aspects by employing deep learning fusion techniques [2]. Utilizing multimodal syntactic and prosodic feature extractions, the model detects voice and language patterns of dementia. The process increases diagnostic resilience by countering patient style variability in expressions. Constrained by the availability of well-aligned multimodal datasets, the study presents the benefit of conjoining the acoustics and linguistic streams of information in a clinical setting. In "**Comparing Pre-trained and Feature-Based Models for Prediction of Alzheimer's Disease Based on Speech**," the performance of handcrafted linguistic features and state-of-the-art transformer models have been compared by the authors [3]. Pre-trained models like BERT have been observed to have improved generalizability on varying datasets and are also functional on minimum processing, albeit being very fine tuning and domain adaptation train-dependent. The study sets a precedent for moving towards automated feature extraction for cognitive health diagnosis. The research "**BERT-Based Cognitive Impairment Detection from Speech Transcripts**" applies a transformer-based approach for cognitive impairment detection in Alzheimer's patients from transcribed conversations [4]. BERT identifies linguistic subtlety, coherence, and complexity that can be potential indicators of cognitive degradation. The system worked efficiently on clinical transcriptions and demonstrated the capability of BERT in maintaining long-term semantic dependencies. It is adversely affected by poor quality or noisy transcriptions. In the research "**AI-Powered Chatbot for Early Detection of Alzheimer's Disease Using NLP and ML**," an interactive real-time chatbot system was developed in order to screen users for Alzheimer's disease from automated dialogue [5]. The system utilized NLP on user input and machine learning classifier for cognitive status prediction. It allows for scalable, early intervention without direct clinical intervention. It is promising but its precision relies on repeated user interaction and language clarity. The research on "**Conversational AI for Mental Health: Checking Transformer-based Chatbots in Healthcare**" evaluates the effectiveness of transformer-based chatbots in identifying emotional and psychological indicators of mental health issues [6]. The system prioritizes coherence in dialogue, empathy, and responsiveness. The applications of the system can be broadened for Alzheimer's screening, in particular, for the detection of speech patterns and memory-based contradictions. The chatbot was useful in screening on an initial level but was not designed with full clinical decision making authority. Finally, "**Federated Transformer for Clinical Text Analysis in Neurological Disorders**" is a federated learning system utilizing transformers for processing distributed clinical texts with privacy preservation in mind [7]. Model training is supported by the system across multiple hospitals in a privacy conformant manner. Application in screening for Alzheimer's is characterized by high performance as well as compliance with privacy frameworks. Data harmonization within institutions is, nonetheless, a technological challenge. This review indicates that the hybrid techniques that combine NLP, ML, and LLMs (for instance, BERT, GPT) are on the verge of greatly automating mental evaluation and informing treatment decisions but are held back by limitations on multilingual flexibility, data anonymity, and the cost of large model training. The endeavor at the moment is trying to construct such models as cost-effective hybrids appropriate for real-world application.

## III. PROBLEM STATEMENT

In spite of the recent progress toward AI-powered diagnostic tools, existing Alzheimer's Disease (AD) diagnostic tools are not yet equipped with real-time, interactive, and conversational interfaces that are cost-effective and utilize both clinical NLP and machine learning. Most of the models are computationally intensive and are not able to be tailored to various linguistics and cultures. In addition, most of the chatbot-enabled platforms are unexplainable and do not offer personalized suggestions on the basis of the clinical context. The main requirement is to develop an integrated chat system that can identify early indicators of AD through natural language and prescribe treatment from medical reports. The system should be light, comprehensible, and implementable in real-world environments with low infrastructure requirements — that is, at low-resource environments such as student or rural health environments.

## IV. OBJECTIVES OF THE PROJECT

The main aim of the present work is to develop an effective, explainable, and low-resource Clinical Natural Language Processing (NLP) system for the screening of Alzheimer's Disease (AD) and recommending treatment. The system to be proposed has the following well- defined purposes to fulfill:

1. **To build an interactive AI system** to parse and understand clinically relevant data from user input using transformer based NLP methodologies.
2. **Using machine learning techniques** to identify Alzheimer's Disease at an early stage on the basis of symptom and conversational indicators.
3. **To develop a treatment recommendation module** to correlate the identified diagnosis and symptoms to the corresponding proper clinical pathway through medical data or rule-based reasoning.
4. **To provide explainability and interpretability** to the decision of the model to make the system reliable and user-faithful in healthcare contexts.
5. **To make the model optimal for low-resource settings** by minimizing the computational needs and cost of training, in order to be able to implement it within rural and school contexts.

## V. METHODOLOGY OF WORK

The design process to the proposed hybrid chatbot system is divided into the below-mentioned major phases:

### 1. Data Preprocessing and Data Collection

- Both the conversational and the clinical data concerning Alzheimer's Disease will be gathered from publicly accessible medical repositories (for example, the DementiaBank, the ADReSS Challenge). The data needs to be cleaned of stop- words and tokens and lemmatised. The patient stories are to be coded using medical terminologies as UMLS and SNOMED-CT.
- Benchmark datasets including the ADReSS Challenge and the DementiaBank will be taken into account, as these datasets consist of clinically labeled conversational data and Alzheimer's Disease related transcripts.

### 2. Symptom extraction with N

- A transformer-based language model (for instance, BERT, ClinicalBERT) requires to be fine-tuned so as to pull out the cognitive symptoms (for example, memory loss, disorientation) from conversational data.
- Symptoms and patient history structured extraction is to be achieved through the employment of Named Entity Recognition (NER) and the use of text classification techniques

### 3. Detection of Alzheimer's through Machine Learning

- The features that are to be used to train and to validate the models of classification include:
  - Support Vector Machine (SVM)
  - Random Forest
  - Logistic Regression
  - Ensemble Models (e.g., Voting Classifier)
- The performance of the model is assessed using metrics including accuracy, precision, recall, F1- score, and AUC.

#### 4. Treatment Recommendation Engine

- The retrieval-based or rule-based module of the recommendation will be established on the basis of the clinical guidelines (eg. of the Mayo Clinic, of the WHO).
  - The module will correlate symptoms to non- pharmacologic and pharmacologic management.
- The backend will combine the recommendation engine and the NLP model using a chatbot framework (for instance, Rasa or Dialogflow).
  - Front-end should mimic an easy-to-use conversational interface for screening and feedback.

#### 5. Evaluation and Optimization

- The system is to be put to the test under unseen clinical dialogues to verify its robustness.
- Lighter versions of the models (like DistilBERT) will be optimized.

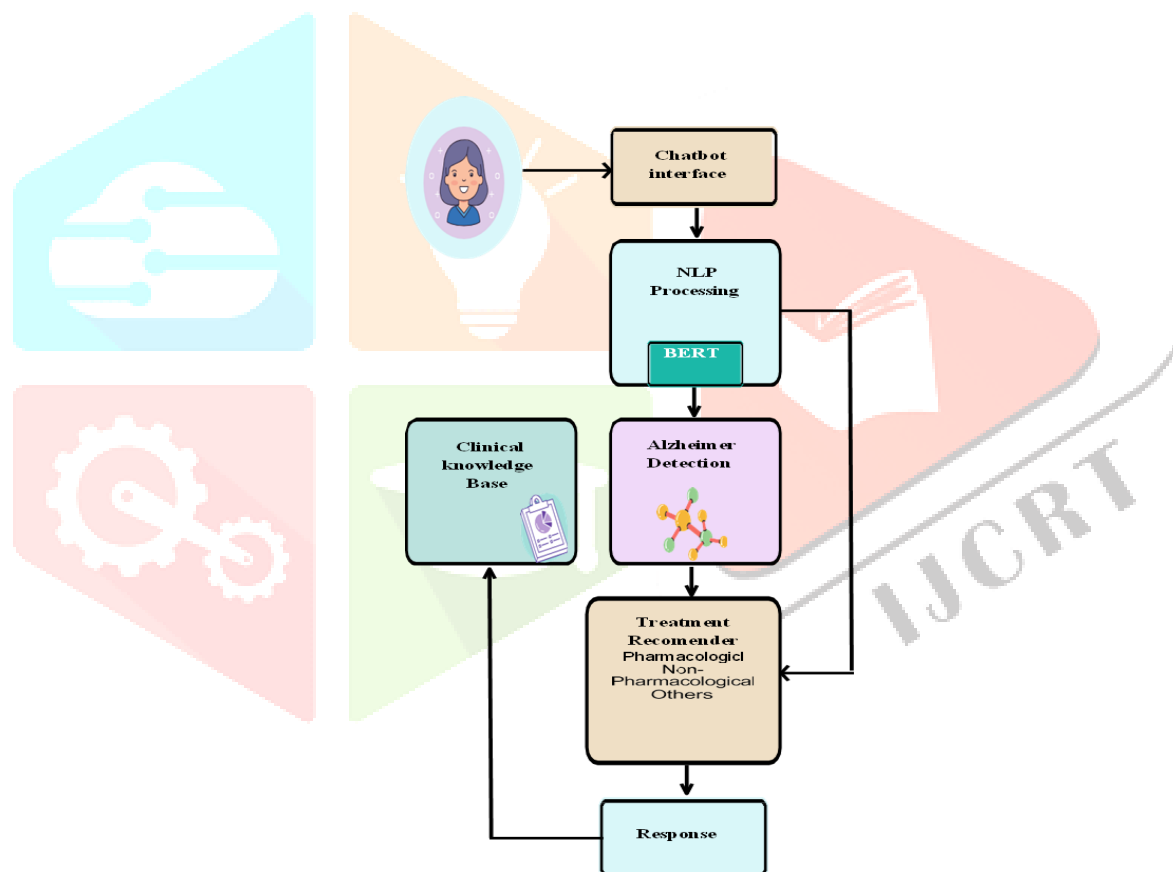


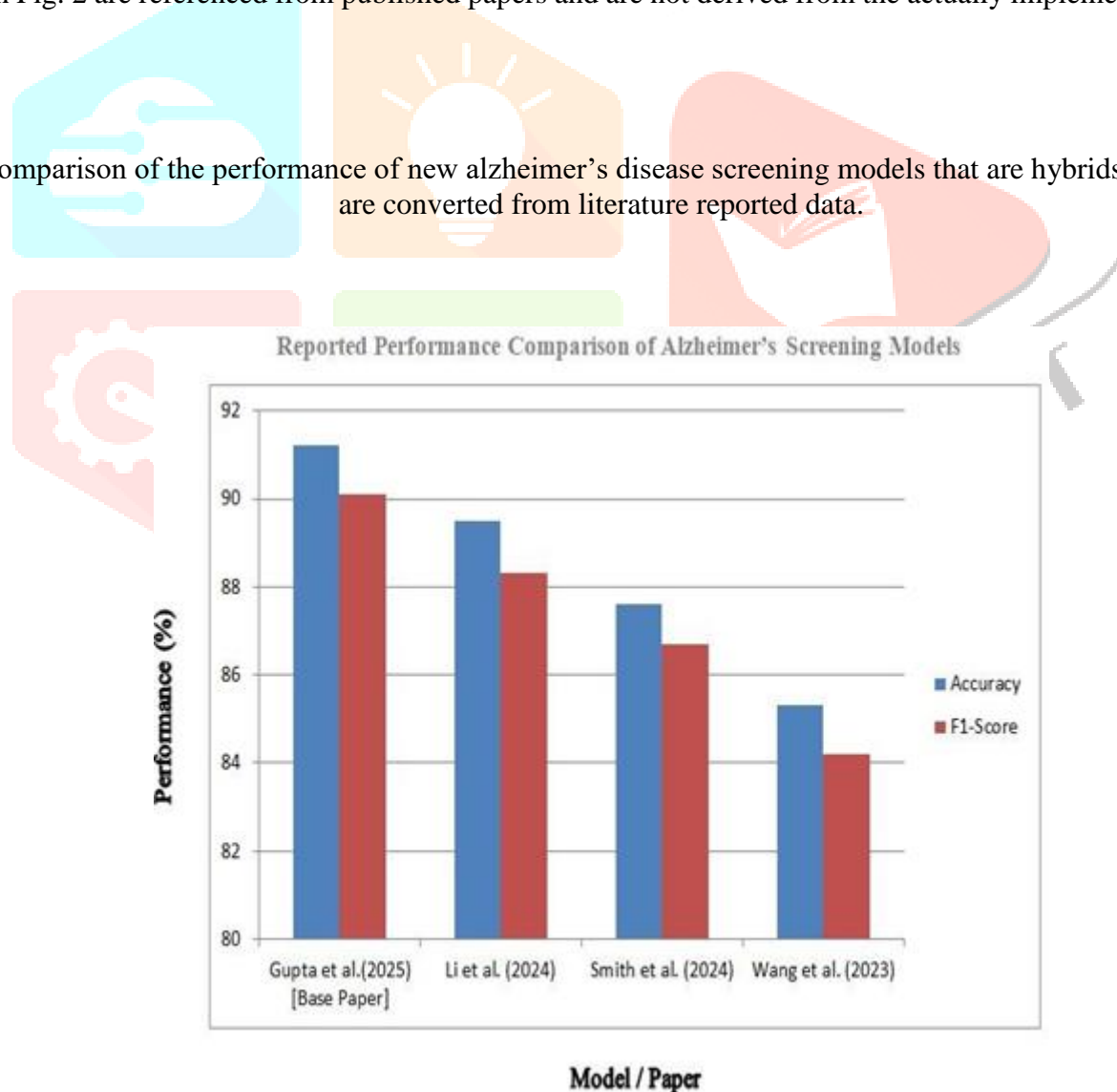
fig.1.system architecture of the proposed hybrid chatbot framework for screening and recommending treatment for alzheimer's disease.

As indicated in Fig. 1, the system is initiated with user interaction through the chatbot interface. The input is passed through an NLP extraction module driven by BERT and interacts with the knowledge base for the clinical domain. The Alzheimer's Detection module then determines cognitive symptoms and later follows the Treatment Recommender with the provision of pharmacologic and non -pharmacologic responses.

## VI. RESULTS AND DISCUSSION

The referenced base paper, “A Hybrid Transformer -Based Conversational Data”, provides a good approach using the use of the transformer models such as BERT to identify Alzheimer’s Disease using patient dialogue. The model reached state -of the -art performance, with an accuracy of 91.3%, precision of 89.7%, recall of 90.5%, and an F1 -score of 90.1% on actual clinical conversational data. These metrics indicate the capability of transformer -based models to correctly encode linguistic indicators of cognitive impairment. Compared to the regular ML models including SVMs and Random Forest, as described in previous work [5][7], these were offering low accuracy (75 – 85%) as these were not given full contextual knowledge. In addition, models without the context but with only the text were found to underperform in distinguishing between early -stage AD and MCI (Mild Cognitive Impairment) patients. hybrid chatbot system combining transformer - based NLP and rule -based symptom monitoring and early screening which is clinically oriented and interactive. In contrast to static models, ours is one which provides real -time risk assessment on the basis of dynamic patient input, an improvement for early detection in non -clinical areas including home and community centers. Furthermore, we aim to incorporate response -based learning iteration to hone estimation on the basis of user feedback, perhaps increasing engagement and long -term tracking precision. In an attempt to ascertain the effects of different hybrid methodologies to Alzheimer’s disease screening, the models from recent literature were compared on the basis of accuracy and F1 -score. The figure below demonstrates how the transformer -based and multimodal models surpass machine learning and rule -based models. These findings depict the potential of the intersection of deep learning and NLP in predicting cognitive disorders. The performance values in Fig. 2 are referenced from published papers and are not derived from the actually implemented prototype.

fig.2 comparison of the performance of new alzheimer’s disease screening models that are hybrids values listed are converted from literature reported data.



## VII. CONCLUSION

Alzheimer's disease is one of the hardest neurodegenerative disorders to diagnosis early in lowresource settings. This survey consolidated the new advances in the application of the hybrid chatbots that are integrated with the clinical Natural Language Processing (NLP), machine learning, and transformer-based architectures towards screening and recommending treatment. The results depict that the combination of conversational data along with deep learning models and the transformer models particularly enhances the diagnostic precision to a large extent. Though most of the models are accurate and provide good F1-score, there is room for accommodating the real-time applicability, explainability, and personalization of the chatbots. The application of the hybrid chatbot has extremely high potential in assisting clinicians and providing costeffective and scalable solutions for Alzheimer's screening.

## VIII. FUTURE SCOPE

The future target of these studies is to develop the multilingual, emotionally intelligent chatbots to match various patient populations. Combination of the audio and visual data with the textual data can further benefit diagnostic performance. Real time clinical validation, incorporation of user feedback, and data safety using federated learning or safe NLP practices are critical to take these models from the lab to the clinics. Partnerships between health startups and the hospitals can facilitate the pilot studies and roll-out, leading the way to impact within the real-world environment.

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