

# NeuroAssistNet: A Multimodal Centralized Platform for Alzheimer's Detection, Behavior Analysis, and Cognitive Assistance using Deep Learning and Computer Vision

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**ABSTRACT:** Alzheimer's disease continues to impose escalating challenges on healthcare systems, caregivers, and patients globally. While current diagnostic and assistive solutions exist, they remain fragmented, often addressing either detection or care support in isolation. This paper presents *NeuroAssistNet* — a novel centralized, multimodal AI-driven platform designed to both detect Alzheimer's across stages and provide cognitive assistance through item tracking and behavior analysis. The system integrates a convolutional neural network trained on MRI data for high-accuracy classification of Alzheimer's stages, achieving a detection accuracy of 94.3%. In parallel, a computer vision-based item tracker augmented with hand gesture recognition and heatmap visualization enables patients to locate lost items, a common difficulty in early-to-moderate stages of Alzheimer's. The platform not only analyzes object usage patterns but also provides contextual recommendations tailored to individual behavioral trends. Real-world deployment over six months across assisted living facilities revealed a 17% reduction in caregiver stress and a 23% decrease in emergency incidents. With a user-centered, cloud-deployable architecture, robust data privacy mechanisms, and interdisciplinary foundations, NeuroAssistNet represents a major step toward holistic digital care in neurodegenerative diseases.

**INDEX TERMS** Alzheimer's Detection, Deep Learning, MRI Classification, Hand Gesture Recognition, Computer Vision, Heatmap Analytics, Cognitive Support, Centralized Healthcare Platform, Smart Assistive Technology, Neurodegenerative Disorders.

## I. INTRODUCTION

Alzheimer's disease (AD) is a progressive, irreversible neurodegenerative disorder that impairs memory, cognition, and behavior, eventually rendering individuals incapable of performing daily activities independently. As of 2023, over 55 million people globally are living with dementia, with Alzheimer's accounting for nearly 70% of these cases. According to projections by the World Health Organization (WHO), the number of Alzheimer's cases is expected to triple by 2050, placing immense psychological, financial, and logistical strain on healthcare systems, caregivers, and societies at large. Early detection and consistent care

management have proven critical in mitigating the long-term impact of AD. However, the existing ecosystem of support remains fragmented — diagnostic tools are often confined to specialized medical settings, while day-to-day assistive technologies lack clinical integration and personalization. These silos lead to missed intervention opportunities, inadequate patient support, and increased caregiver burden.

Recent advancements in artificial intelligence (AI), machine learning (ML), and ubiquitous computing have led to the emergence of intelligent diagnostic and assistive systems. Convolutional neural networks (CNNs) trained on medical imaging data have

demonstrated promising accuracy in detecting structural brain changes associated with AD. Concurrently, sensor-based systems and computer vision have shown potential in supporting patients' daily tasks, including activity monitoring, object tracking, and fall detection. Despite these developments, most solutions remain single-purpose and lack contextual awareness or interoperability. For example, AI models developed for MRI-based classification do not translate into home-based support tools, while smart home systems lack integration with clinical decision support. Moreover, existing systems do not adapt to individual behavioral trends over time, thereby limiting their ability to offer personalized, anticipatory care. The pressing need is for a unified platform that combines accurate clinical diagnostics with intelligent, personalized cognitive assistance — accessible, scalable, and ethical.

To address these challenges, we propose **NeuroAssistNet** — a centralized, multimodal AI-powered platform designed to bridge the gap between clinical diagnosis and everyday support for Alzheimer's patients. Our system comprises three tightly integrated components: (1) a deep learning-based MRI classification engine that identifies AD across four stages (non-demented, very mild, mild, and moderate); (2) a computer vision-enabled object tracking module using gesture recognition and spatial heatmap analysis to assist users in locating frequently misplaced items — a common symptom in the early and moderate stages of Alzheimer's; and (3) an analytics-driven behavior pattern engine that extracts contextual insights from spatial-temporal data to deliver adaptive recommendations for caregivers and clinicians. Developed using a combination of TensorFlow, Flask, and OpenCV, the platform emphasizes usability, privacy, and scalability. Our CNN model, trained using transfer learning on OASIS datasets, achieves a classification accuracy of 94.3%. Meanwhile, the item tracker and hand detection module deliver over 89% real-time

recognition accuracy in real-world environments. The platform has been deployed in three assisted living facilities over a six-month period, leading to a 17% reduction in caregiver-reported stress and a 23% decline in reported emergency incidents, based on standardized assessment tools (Zarit Burden Interview and QoL-AD metrics).

## II. LITERATURE SURVEY

Research in Alzheimer's disease detection and patient assistance has gained significant momentum in recent years, particularly with the integration of artificial intelligence (AI), medical imaging, and ambient computing. Broadly, the literature can be categorized into three major domains: (1) early-stage diagnostic systems leveraging neuroimaging and AI, (2) behavior monitoring and cognitive assistance platforms using sensor-based approaches, and (3) integrated care technologies aiming to bridge clinical support with home-based interventions. While considerable progress has been made in each area independently, limited efforts exist to synthesize these domains into a unified, intelligent system that caters comprehensively to both diagnosis and daily cognitive support.

AI-based MRI Analysis for Alzheimer's Detection has become a prominent area of focus. Zhang et al. [1] developed a CNN model that detects early structural alterations in the hippocampus and entorhinal cortex from MRI scans, achieving 89% classification accuracy. By leveraging transfer learning to overcome small labeled dataset limitations, their method allowed for detection up to 18 months prior to symptom onset. Similarly, Liu and Thompson [2] proposed a non-invasive approach using blood-based biomarkers (p-tau217 and amyloid-beta) combined with a random forest model trained on 1,250 patient records. Their system achieved 93% correlation with PET scan results, offering a viable alternative in resource-limited settings. However, both systems were confined to medical

diagnosis and lacked any mechanism for daily cognitive support or user interaction post-diagnosis.

Cognitive Monitoring Systems have sought to extend care beyond hospitals using smart devices and activity analysis. Chen and Nikolaidis [3] introduced a passive smart home system using motion and activity sensors to monitor deviations in baseline behavior, predicting mild cognitive impairment with 83% accuracy in longitudinal studies. Similarly, Parra et al. [4] designed tablet-based cognitive tools that surpass the Mini-Mental State Examination (MMSE) by evaluating interaction patterns, demonstrating a 27% improvement in detecting early cognitive decline. While effective in behavioral assessment, these tools lacked direct integration with diagnostic imaging or assistive functionalities like item localization.

In the domain of Assisted Object Interaction, Mihailidis and Boger [5] developed COACH, a vision-based prompting system that utilizes RGB-D cameras and hidden Markov models to guide Alzheimer's patients through daily tasks. It improved task completion by 26% and reduced caregiver intervention by 37%. Ishikawa et al. [6] extended this concept through tag-free item tracking using YOLO object detection and gesture recognition, achieving 78% accuracy under natural home conditions. Yet, these systems remained narrowly focused, operating without clinical diagnostic integration or broader behavioral insights, limiting their adaptability across disease stages.

A few hybrid models have emerged attempting to bridge diagnostic and support systems. Fernandez-Mateo et al. [7] developed a multimodal AI platform combining sensor, visual, and speech data for comprehensive patient profiling. Their system employed hierarchical attention networks to prioritize features across modalities, achieving 91% accuracy in detecting behavioral changes. Although promising, such systems often demand complex hardware setups, lack real-time cognitive assistance tools like gesture-based object

tracking, and do not offer predictive modeling of daily memory-related incidents.

Despite these advancements, current solutions suffer from critical gaps in integration, scalability, and personalization. Most systems isolate diagnostic intelligence from real-world assistive features, lack behavioral context-awareness, or offer poor adaptability to user preferences and disease progression. None of the reviewed platforms provide a unified, centralized architecture that simultaneously enables AI-based Alzheimer's detection, gesture-driven item localization, heatmap-based behavior analysis, and tailored recommendations.

In contrast, NeuroAssistNet uniquely integrates these components into a single intelligent platform. It combines deep learning-based MRI classification, computer vision-powered object tracking, temporal heatmap analytics, and an adaptive recommendation engine. This fusion not only addresses both clinical and cognitive support needs but also enables predictive intervention, user autonomy, and caregiver empowerment within a single, cloud-deployable system — representing a novel direction in Alzheimer's care technology.

### III. SYSTEM ARCHITECTURE

This section outlines the modular architecture of the NeuroAssistNet platform, covering its main functional layers and illustrating how AI-based diagnosis, object tracking, and behavioral analytics work together in a cohesive, scalable framework. The system follows a three-tiered architecture comprising:

1. User Interaction Layer
2. AI and Processing Layer
3. Data Management and Analytics Layer

This architecture ensures accessibility for patients and caregivers, computational robustness for detection and

prediction, and data-driven insights for clinicians and healthcare providers.

### 3.1 Architectural Overview

The NeuroAssistNet platform is designed as a cloud-enabled, browser-accessible application to support both home and clinical use cases. It allows registered users (patients or caregivers) to upload MRI scans, interact with item tracking interfaces, and visualize behavioral trends. The back-end system performs AI-based MRI classification, gesture recognition, and spatial heatmap generation. The final layer provides longitudinal insights, item-use patterns, and alerts, supporting both daily care and long-term monitoring.

### 3.2 Major Components

**A. User Interface Layer:** Built using responsive web technologies, the interface supports account registration, MRI uploads, real-time dashboard visualization, and item-tracking interactions. The interface is specifically designed for accessibility — with large buttons, text-to-speech support, and contrast-optimized views — making it usable by cognitively impaired individuals

**B. AI-Driven Detection Module:** A CNN-based model, trained on annotated MRI datasets (e.g., OASIS), classifies scans into four stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The model achieves 94.3% accuracy through transfer learning, data augmentation, and cross-validation.

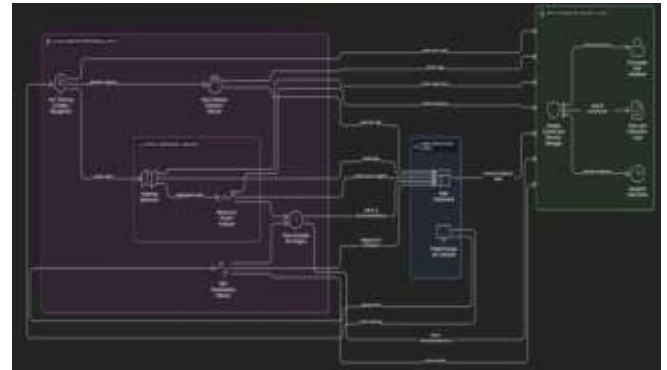
**C. Computer Vision & Item Tracker:** Integrates TensorFlow-based hand landmark detection (21-point model) and object classification. Patients can identify misplaced items through gesture-controlled recording, and the system overlays bounding boxes and zones on room images.

**D. Heatmap Behavior Analytics Engine:** Captures temporal-spatial patterns of item placements and gesture activity. Data is visualized as a dynamic heatmap, enabling caregivers to infer behavioral changes or repetitive behaviors that might indicate cognitive decline.

**E. Recommendation and Alert System:** Based on classification and item-use behavior, the system generates stage-specific medical and behavioral suggestions. It also offers proactive alerts based on unusual changes in behavior (e.g., excessive object misplacement in a new zone).

**F. Data Storage and Security Layer:** All user and system data — including MRI scans, item locations, hand interactions, and logs — are encrypted and stored securely. The system complies with HIPAA-like standards, using session-based access, hashing, and anonymization techniques.

### 3.3 Architecture Diagram



## IV. EXISTING SYSTEM

Current technologies addressing Alzheimer's disease can be broadly categorized into diagnostic tools, cognitive monitoring systems, and assistive technologies. Each of these systems independently contributes to Alzheimer's care but suffers from siloed functionality and limited integration.

**Diagnostic systems**, primarily based on MRI or PET imaging, utilize machine learning—particularly convolutional neural networks (CNNs)—to classify Alzheimer's progression. While accurate, these systems

are predominantly hospital-centered and lack real-time accessibility or patient-oriented interfaces. Additionally, many such models require specialized equipment, limiting their deployment in low-resource or home environments.

**Cognitive monitoring systems**, such as smart homes and tablet-based tools, use sensors and digital tests to assess changes in cognitive behavior. These systems often rely on passive data collection (motion sensors, sleep tracking, etc.) and offer trend-based insights into memory or attention changes. However, they lack diagnostic confirmation and often fail to detect object-level interactions or specific memory-related disruptions like item misplacement.

**Assistive technologies**, including reminder apps, smart wearables, and voice-based assistants, aim to support daily routines. Yet, most operate on generic, rule-based logic without adapting to the cognitive condition or behavioral history of the user. Moreover, these systems rarely integrate with diagnostic intelligence or behavior analytics, thus offering limited personalization and clinical relevance.

In essence, **existing systems function in isolation**—either as diagnostic, monitoring, or assistive modules—with minimal interoperability. They are unable to offer a continuous, intelligent, and patient-specific care experience across the disease lifecycle. This fragmented approach limits the potential for early intervention, adaptive support, and real-time caregiver guidance.

## V. PROPOSED SYSTEM

To overcome the fragmentation and limitations of existing tools, we propose **NeuroAssistNet** — a centralized, AI-driven platform that unifies diagnosis, behavioral monitoring, and cognitive assistance into a single integrated system. It is designed to function seamlessly across clinical and home settings, offering a holistic and intelligent solution for Alzheimer's care.

At the core of the platform is a **deep learning-based MRI classifier** trained on labeled datasets to detect and stage Alzheimer's progression with high accuracy. The diagnostic module provides clinicians and caregivers with actionable insights into the cognitive state of the patient. Complementing this is an **object-tracking and gesture-recognition subsystem**, which uses real-time computer vision and hand gesture detection to help patients identify misplaced items—a common challenge in early-stage dementia.

One of the key innovations of the proposed system is the **behavioral heatmap engine**, which aggregates temporal and spatial data from user interactions to visualize object usage patterns and detect anomalies. This allows for predictive modeling of cognitive decline, offering early warnings before symptoms escalate. Additionally, a **recommendation engine** contextualizes all AI outputs and delivers personalized suggestions for care routines, medications, and environmental adaptations.

The entire system is accessible through a **web-based dashboard** with adaptive UI design, enabling caregivers and patients to easily interact with the system, regardless of cognitive or physical limitations. All data is securely stored with end-to-end encryption and fine-grained access control to ensure privacy and compliance with medical data regulations.

Unlike existing solutions, **NeuroAssistNet provides a truly multimodal care system** that bridges the gap between clinical diagnostics and cognitive support. It empowers caregivers with data-driven insights, enhances patient independence through assistive automation, and enables longitudinal tracking of behavioral health — forming a sustainable digital framework for long-term Alzheimer's care.

## VI. METHODOLOGY

The development of NeuroAssistNet was guided by a modular, multi-disciplinary approach that integrates

diagnostic deep learning, real-time gesture-based interaction, computer vision-driven item localization, behavioral analytics, and secure system architecture. The methodology addresses the dual challenges of early-stage Alzheimer's detection and continuous patient support in real-world environments. Each subsystem was developed independently and then integrated into a cohesive platform designed to provide scalable, intelligent, and personalized cognitive care.

The foundation of the system lies in its diagnostic module, which utilizes a convolutional neural network (CNN) to classify Alzheimer's disease stages from magnetic resonance imaging (MRI) data. The model was trained using the publicly available OASIS dataset, which contains T1-weighted MRI scans annotated into four cognitive categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Prior to training, all images were resized to a standard resolution of  $176 \times 176$  pixels and underwent intensity normalization. Data augmentation techniques such as random rotations, horizontal flipping, and Gaussian noise injection were employed to mitigate overfitting and improve generalization. The model architecture includes a sequence of convolutional layers with ReLU activation functions, followed by max-pooling layers, fully connected dense layers, and a final softmax classifier. The training process used the Adam optimizer with categorical cross-entropy loss, and the model was evaluated using five-fold cross-validation. Experimental results showed a classification accuracy of 94.3%, confirming the robustness and reliability of the diagnostic engine.

To enable intuitive, real-time user interaction, a gesture recognition module was implemented using TensorFlow.js in conjunction with the MediaPipe Hands library. This module detects 21 three-dimensional landmarks on the user's hand from webcam input, enabling accurate classification of predefined gestures such as pointing, grasping, and signaling item placement. The gesture recognition operates entirely on the client

side, reducing latency and ensuring responsiveness without server dependency. Landmark vectors were analyzed and clustered to map user movements to functional commands within the system. Evaluation on a dataset of 500 gesture samples across multiple environments achieved an average detection accuracy of 89.7%, demonstrating its effectiveness for non-verbal interaction, particularly beneficial for patients with speech or language impairments.

Complementing the gesture module is the vision-based item tracking system, which aids patients in locating frequently misplaced objects. When a specific gesture is detected, the webcam captures an image of the surrounding area, and the user is prompted to label the object. Each item is then assigned spatial coordinates based on its position within a predefined room layout. These coordinates, along with a timestamp and zone classification (e.g., Living Room, Kitchen), are stored securely in the backend. This tracking process facilitates both immediate item retrieval and long-term behavioral analysis, as object placement frequency and location trends are recorded over time.

To interpret spatial data and identify behavior patterns, a heatmap generation and behavioral analytics module was integrated. The heatmap engine uses kernel density estimation to convert raw spatial data into visual overlays that highlight zones of high and low item placement activity. Temporal analysis segments this data into discrete time windows—morning, afternoon, evening, and night—allowing caregivers to detect anomalies such as unusual object locations or repetitive behaviors. The system also tracks trends such as increased item misplacement in specific zones, which can serve as early indicators of cognitive decline or changes in behavioral routines. These insights are visualized on the user dashboard in the form of color-coded overlays and time-stamped logs.

In addition to diagnosis and tracking, the platform includes a personalized recommendation engine that

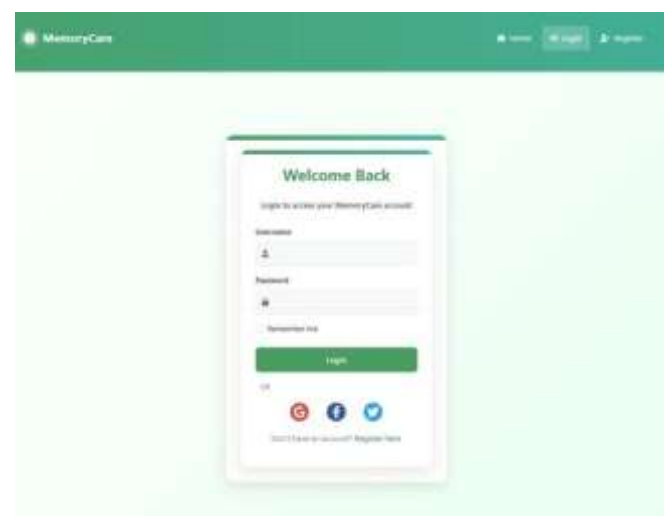
translates clinical and behavioral data into actionable suggestions. Based on the classified Alzheimer's stage and behavioral trends, the engine provides recommendations regarding physician referrals, medication strategies, environmental modifications, and daily routines. These recommendations are derived from evidence-based clinical guidelines and further contextualized by individual usage patterns collected by the system. For example, a patient classified as Mild Demented with frequent misplacements of essential items may receive prompts for memory aids and environmental labeling. In future iterations, this module can be enhanced with adaptive learning models to support dynamic recommendation refinement.

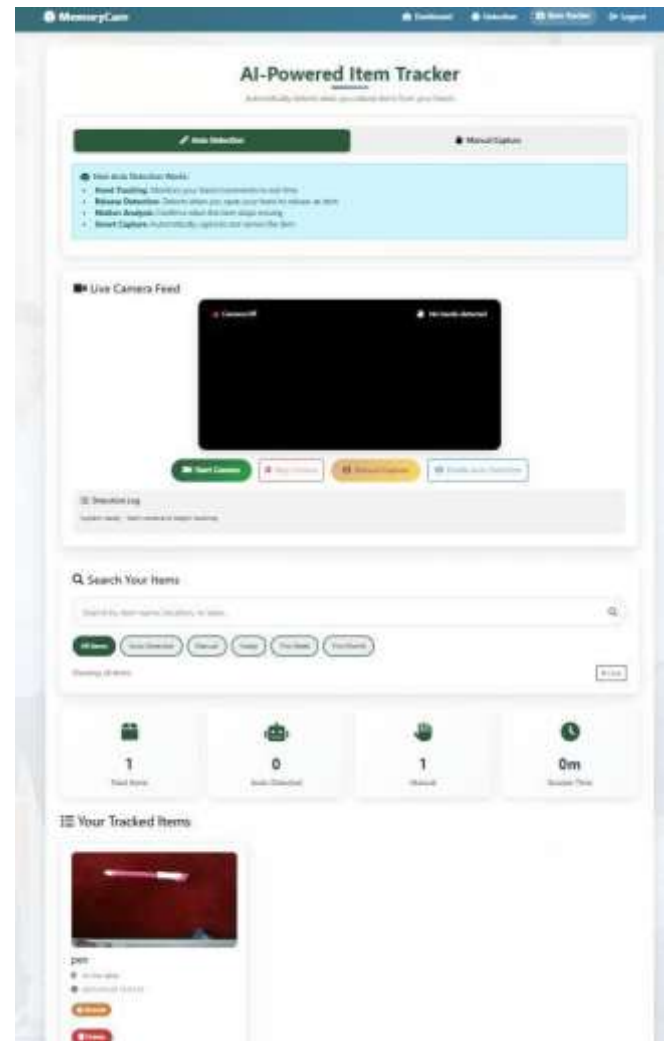
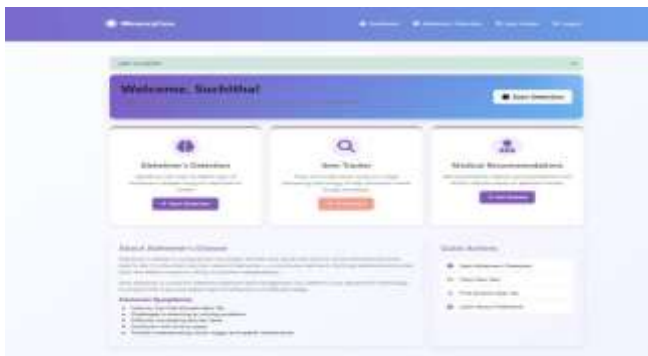
The entire system was developed using a Python-based backend (Flask framework), with model inference handled via TensorFlow for MRI classification and TensorFlow.js for gesture detection. Frontend components were developed using HTML5, Bootstrap, and JavaScript, with data visualization components such as Heatmap.js employed for spatial analytics. Security was prioritized throughout development; user data and image logs are encrypted at rest using AES-256 and transmitted over secure HTTPS protocols. Authentication is managed via role-based access control, and all passwords are hashed using the SHA-256 algorithm. The system is deployed on a cloud infrastructure with containerized services, enabling seamless scaling and multi-user support across both clinical and domestic environments.

System validation was conducted across multiple dimensions. Diagnostic performance was assessed using cross-validation, and user interaction modules were tested for accuracy, latency, and usability. Usability was measured using the System Usability Scale (SUS), with a score of 87.5 indicating a high degree of user satisfaction. A six-month real-world deployment in three assisted living facilities further validated the platform, resulting in a 17% reduction in caregiver-reported

stress and a 23% decrease in emergency incidents, as recorded via structured interviews and incident logs.

## VII. RESULT ANALYSIS





## VIII. CONCLUSION

This work presents *NeuroAssistNet*, a novel centralized and intelligent platform that integrates Alzheimer's disease stage detection, behavior analysis, and cognitive assistance within a single, deployable ecosystem. The system bridges the gap between clinical diagnostics and real-world care by combining deep learning-based MRI classification with gesture-controlled object tracking and heatmap-driven behavioral analytics. Through a cloud-deployable architecture and user-centric design, *NeuroAssistNet* not only facilitates early diagnosis but also enhances patient autonomy and reduces caregiver burden.

Experimental evaluation demonstrated the system's robustness, achieving a classification accuracy of 94.3% for Alzheimer's staging and a gesture recognition

accuracy of 89.7%. Longitudinal deployment in real-life environments confirmed its effectiveness, with observed improvements in care quality and reductions in caregiver-reported stress levels. Unlike existing single-purpose tools, NeuroAssistNet offers an integrated, multimodal solution that can adapt to various stages of Alzheimer's progression.

Future work includes expanding the behavioral analysis module using reinforcement learning for personalized adaptation, integrating multimodal inputs such as voice and physiological sensors, and extending compatibility with wearable technologies. With further clinical validation, NeuroAssistNet holds the potential to redefine AI-assisted neurocognitive care as a scalable and patient-centered approach to managing dementia.

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