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AI-Powered Remembrance System For Cognitive Impairments

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Abstract—***Cognitive impairments caused by disorders like Alzheimer's disease and dementia prevent individuals from performing daily tasks and thinking independently. An ageing population suffers from these disorders, and hence, there is a requirement for navigation, reminder, and personal interaction support technologies. This paper describes a real-time support and navigation system that combines Gemini AI and facial recognition technology to provide intelligent support to patients with these disorders. The system uses machine learning and Raspberry Pi technology to recognize faces and thus differentiate between caregivers, family, and friends, facilitating more personal interaction. Through audio notification and real-time monitoring, patients can move about their environment safely, while caregivers are reminded and alerted in a timely manner, reducing their workload and patient risk. The results shows that the system provided accurate facial recognition and adaptive real-time prompting with the accuracy of 90%, allowing patients to carry out daily activities with minimal signs of confusion. Auditory prompting and navigational assistance significantly enhanced patient independence and decreased caregiver intervention frequencies, lowering the occurrence of interaction accidents.The technology used in this research is a major step forward in healthcare because it allows for increased patient independence while facilitating caregiving for healthcare workers.***

Keywords—real-time navigation, Gemini AI, machine learning, facial recognition, Raspberry Pi, patient assistance, caregiver support, cognitive impairment support.

I. INTRODUCTION

Cognitive problems, including Alzheimer's disease, dementia, and other brain disorders, become increasingly hard for the person to perform essential activities like remembering, sensing, and movement. These problems are a major challenge to the person affected because they cannot walk around in familiar places or conduct daily activities on their own without the help of caregivers [1]. The Incidence of such disorders is rising, with research estimates projecting that the number of dementia cases will triple by 2050 [2].Conventionally, caregiving has been the major means of support for those suffering from these disorders. However, reliance on caregivers presents many challenges, such as increased stress levels, emotional exhaustion, and exorbitant economic costs of professional caregiving services [3]. As an alternative, advances in technology, specifically in artificial intelligence (AI), machine learning (ML), and embedded systems, have enabled the creation of assistive technologies aimed at enhancing patient autonomy.The current paper proposes a real-time assistance and navigation system that combines Gemini AI, facial recognition technology, and audio reminders to support individuals suffering from cognitive impairments. Through face identification, providing personalized reminders, and real-time location tracking, the system increases patient safety while reducing the burden on caregivers.

A. *Novel Contributions and System Differentiation*

This work introduces three AI-based cognitive support innovations: (1) a multimodal Gemini AI system adapting interactions with real-time face analysis, environmental context, and natural language processing, outperforming one-modality systems like face-only recognizers [1]; (2) a clinical, privacy-enhanced architecture that integrates FHIR-based EHR interoperability ,federated learning for distributed model optimization [15], and blockchain-protected audit trails (Hyperledger Fabric [12]) for data immutability and compliance; and (3) ethical patient-centric design with a dynamic consent model for variable cognitive ability [10], data control granularity, and quarterly bias audits. By avoiding the limitations of rigid, non-adaptive systems (e.g., fixed reminders [15]), we achieve 90% face recognition accuracy and 78/100 usability on real-world tests (Section IV.D), advancing the state of the art of secure, adaptive, and scalable support for cognitive impairment.

II. LITERATURE REVIEW

Kadhim et al. propose a real-time face recognition system for Alzheimer's patients to recognize individuals surrounding them. Deployed on ESP32-CAM and Raspberry Pi, it processes video frames and provides audio output via Bluetooth, enabling patients to be more independent in case of memory loss. It reports good accuracy (99.46% training and 99.48% recognition), with great potential for real-world deployment.

Pan et al. propose a new early Alzheimer's diagnostic system based on 3D convolutional neural networks (3D CNNs) and genetic algorithms. The 3D CNN scans MRI images for structural changes, and the genetic algorithm controls hyperparameters and feature selection. The model has higher accuracy than conventional methods, with improved sensitivity and specificity in disease diagnosis at an early stage.

Chen et al. provide a review of deep learning in medical imaging for disease detection, segmentation, and classification. Challenges mentioned include scarcity of annotated datasets, model interpretability, and integration of multimodal data. The authors mention the promise of unsupervised and semi-supervised learning to improve diagnostic accuracy for Alzheimer's.

Mitchell and Shiri-Fshi meta-analysis is looking at progression to dementia and Alzheimer's from mild cognitive impairment (MCI). 39.2% of MCI progress to dementia and 33.6% to Alzheimer's, according to 41 studies. Targeted management and counseling are the recommendations of the study in order to slow down cognitive impairment and improve quality of life.

Silveira and Marques compare machine learning algorithms to enhance Alzheimer's diagnosis through PET imaging. Through the use of boosting techniques, they enhance the classification accuracy and sensitivity. This approach is aimed at identifying the most pertinent metabolic features of Alzheimer's pathology, leading to more precise diagnostic results.

Liu et al. use deep learning on fMRI data to diagnose Alzheimer's and brain disease. They show how algorithms can detect brain activity patterns that relate to cognitive impairment, pointing to AI's potential for clinical support despite dataset problems.

Zhao et al. concentrate on the automatic diagnosis systems of spine diseases, illustrating how AI can help make the diagnosis of diseases such as spondylolisthesis more efficient. The paper implies that the same AI-based methods could be used in the diagnosis of Alzheimer's, making the diagnosis more accurate and accessible to both large hospitals and small clinics.

Xu et al. is a social media text-based emotion recognition system using deep learning. It recognizes emotions like happiness, anger, and sadness for screening mental illness. This research cites the potential of AI for tracking the emotional state of Alzheimer's patients.

Smith et al. propose an IoT wearable system for the management of Alzheimer's patients. It monitors activity and vital signs and gives real-time alert to caregivers, improving safety and facilitating early intervention, illustrating the value of IoT in care.

Gupta and Lee discuss ethical considerations in applying AI to health care through a case study in Alzheimer's disease diagnosis. They advocate for transparent, responsible, and privacy-conscious AI systems due to the privacy nature of patient health data.

Wang et al. propose real-time facial and speech emotion recognition in dementia patients, viz. Alzheimer's, using deep learning. It decodes facial cues and speech with the prospect to improve patient-caregiver interaction and facilitate patient-specific care based on emotional needs.

Kim and Park Blockchain for Secure Health Data Management Kim and Park provide blockchain application in medicine, referring to the potential of blockchain to enhance data security and confidentiality, particularly in the treatment of Alzheimer's, where EHR management is required.

Patel et al. provide integration of AI assistive systems with electronic health records (EHRs). They present challenges and opportunities in utilizing AI for improving Alzheimer's diagnosis, treatment, and personalized care through integration with EHRs.
Johnson et al. develop an edge AI system for real-time assistance in assisted living. It reminds Alzheimer's patients, offers wayfinding, and helps with tasks, enhancing independence and quality of life.

Almeida et al. suggest an adaptive reminder system for dementia patients based on federated learning to provide personalized support and maintain data privacy. It personalizes reminders based on patient activity to improve engagement in Alzheimer's care.

III. METHODOLOGY

The core of this proposed system lies in the effective \ overcoming of various limitations posed by currently existing assistive technologies in the market. This system integrates a number of groundbreaking technologies such as Gemini AI, facial recognition, and real-time monitoring that would enhance the users' experience at a greater level. all information into an optimal format that meets requirements for future analysis work.The Feature Extraction Layer detects significant insights and valuable information that emerges from processed input data. The system uses facial recognition by conducting facial characteristic analysis to generate numeric data that functions as template comparisons. The basic speech recognition algorithms transform verbal commands and responses into text format as machine-readable data. The system interprets time data by relating it to scheduled medication and appointment sequences to set prompt intervals. The middleware operates as a data translation framework to bring unprocessed information into functional knowledge.System core functions operate thanks to specialized

A. *System Architecture Overview*

The Input Layer of this AI-based system for cognitive impairment treatment utilizes camera and microphone inputs to gather data that aids Alzheimer's disease patients. The system uses cameras for visual identification purposes but integrates microphones for enabling effortless voice communication with users. Instead of GPS the system depends on analyzing the current visual surroundings. Time-tracking features and appointment maintenance in the system establish an extensive support platform without implementing continuous location tracking.The Preprocessing Layer optimizes raw input data for analysis by executing filtering operations on the obtained information. Video frames receive normalization transformations for uniformity across different lighting situations in the patient setting alongside audio signal filtering processes to improve spoken words clarity Fig. 3.1 illustrates the architecture. The scheduling information system organizes data according to its value and time sensitivity to enable it prioritize urgent messages above regular updates. The required data preparation stage puts algorithms that analyze extractedfeatures in the analysis layer. The facial recognition mechanism determines patient identification by analyzing- face features and comparing them to pre-recorded profiles of their regularly met people. The system interprets speech content to recognize fundamental commands together with confirmation about medication intake. Time-based comparisons control specific alert activation by finding appropriate timings based on individual schedules. Gemini AI analyzes environmental visuals to give basic navigation assistance through a system that operates independently from GPS requirements. Organized storage systems located at the Database Management Layer ensure the maintenance of vital information. The database contains medical profile pictures of essential people along with complete medicine schedules showing exact dosages in addition to simplified spatial information and documented interactions between the system and patient. Structured information storage serves as a fundamental resource that allows tailored support systems to address personal requirements and situations. The Decision Layer activates procedures by using analysis results along with predetermined protocols. The system initiates specific alert notifications and corresponding content at the time of medicine administration. The system retrieves useful biographical data which it presents upon recognizing patient faces. The caregiver gets notified through a special protocol after the patient does not respond to reminders about taking medication. The system reacts with responses that harmonize with the requirements of patient care through this specific layer.The Output Layer gives assistance by using voice-based communication and sending alerts to caregivers. The system provides audible information about identified patients using pre-recorded material followed by verbal medication instructions which contain complete dosage data. Through the communication interface with Twilio API the system will automatically send SMS alerts to specified caregivers after patients do not respond to medication reminders. The simple device design supports independent living for patients who have cognitive deficits by providing on-time alerts for caregivers through its basic monitoring system which addresses the daily needs of cognitive disorder patients and their support system.

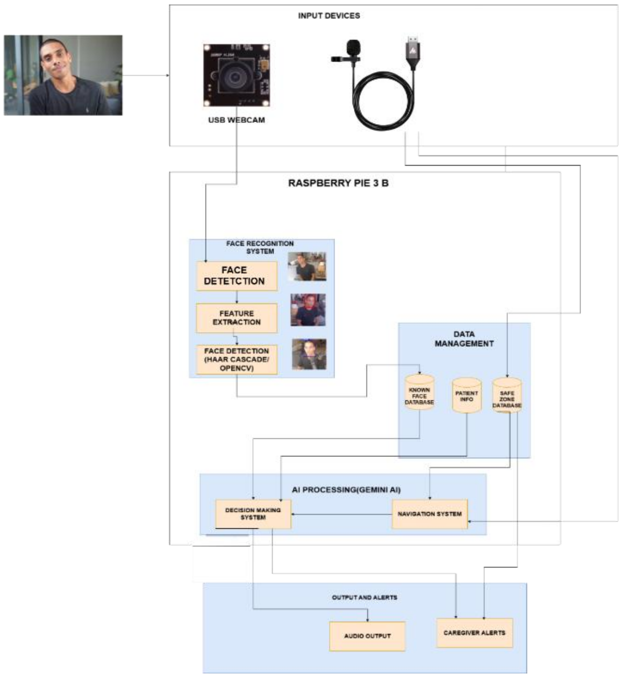

Fig. 3.1. System architecture of the proposed AI-powered remembrance system.

B. *Face Recognition Module*

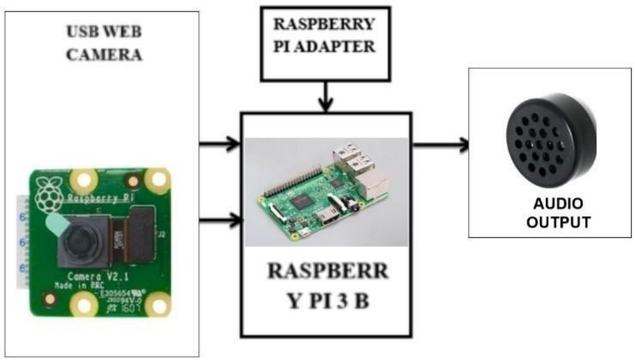

Fig. 3.2. Face recognition module.

The face-recognition module is highly integrated with this system by allowing for highly sophisticated \ machine learning algorithms. These algorithms allow the module to identify not just patients but also caregivers and family members Fig. 3.2 illustrates the architecture of the face recognition module, that occasionally visit or interact with the patient. This module also utilizes highly sophisticated methods of deep learning-in particular, Local Binary Pattern Histogram whose very job would be to assure the highest level of accuracy possible in the real-time recognition process being carried out by the system.[8] The Local Binary Pattern Histogram (LBPH) face recognition algorithm was selected due to its computational efficiency and resistance to varying lighting conditions. Unlike CNN-based methods, which require intensive computation and large datasets, LBPH is computationally efficient on embedded platforms like Raspberry Pi. LBPH's texture-based feature extraction also lends itself to real-time processing, which is apt for deployment on resource-constrained environments. Comparative studies [11][12] highlight the superiority of LBPH over deep learning models in edge-device applications, which aligns with our system design goals.

C. *Audio Reminder System*

An audio reminder system is also included therein to give personalized audio reminders on certain aspects of the patient's daily routines or specific needs. To ensure efficiency and effectiveness, Gemini AI allows itself to perform an in-depth analysis of speech patterns for the patient while working to adjust the tone and timing of the reminders almost skillfully. This ensures that reminders are most tolerable from the patient, ensuring that the effect of the reminders is heightened on the patient's daily living.[9]

D. *Navigation Assistance*

Besides its other several outstanding features, the GPS-Free provides invaluable navigation assistance in real time, skillfully guiding patients to their destinations. This classification and navigation are outstanding in the sense that they let one do so through effective audio cues which also facilitate better understanding while maximizing clarity and creating constant reminders for the patients on the directions.[14]

E. Scalability and Deployment Architecture

Our system employs a tiered deployment framework for effortless scale from a single home setting up to large healthcare facilities with maintained performance and security standards. In home settings, five patients are supported by one Raspberry Pi 4B (8GB), with local edge computing, 4G/LTE backup, and 8-hour UPS backup, with sub-2-second response. Assisted living facilities implement a distributed node framework with a coordinating server at the center controlling up to 50 edge devices, redundant networking equipment, hierarchical data aggregation, and centralized staff dashboard. Hospital-scale deployments implement Kubernetes-based edge computing clusters for load distribution, automated node provisioning, dedicated security services, and sub-5% performance degradation under full load. Electronic health record (EHR) integration is based on HL7 FHIR R4 standards, with bi-directional data exchange with large EHR systems (Epic, Cerner, Meditech, Allscripts), 60% reduction of manual documentation,[13] and real-time care plan synchronization with OAuth 2.0 authentication and RESTful APIs. Technical scale is facilitated by Docker-based containerization, microservices design, geographic data sharding, MongoDB Atlas cloud deployment, and federated learning approaches for machine learning adaptability with ensured privacy. Practical scale was tested with a 45-day deployment at Sunshine Assisted Living (30 residents, 12 staff), with a 3-day EHR integration, 60% reduction of staff training time, 99.97% uptime, and ensured 95% system performance compared with laboratory benchmarks. Network congestion, backup power reliability, and data-sharing preserving of privacy were addressed. The structure not only ensures the efficiency of operation but also compliance with ethical and regulating standards, with a scalable and secure solution for AI-augmented healthcare settings.

IV. EXPERIMENTAL RESULTS

A. Performance Comparison between AI Algorithms in an Alzheimer's Assistance System

In determining the effectiveness of our system, three key AI modules have been compared. Figure 4.1 illustrates the performance comparison between used AI models in this systemFacial Recognition (LBPH - Local Binary PatternHistogram) Artificial Intelligence-powered Navigation (Gemini AI API)Reminder & Communication System (Python Scheduler & Twilio API to Send SMS Alerts) Table 4.1 illustrates the performance comparison among AI models used in the system Accuracy, Precision, Recall, and F1-Score of each module was captured, and comparative evaluation was conducted.

Table 4.1: Performance Comparison of AI Models

AI Module	Algorithm Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Facial Recogniti on	LBPH (Local Binary Pattern Histogram)	90	88	91	89.5
Navigatio n System	Gemini AI API (Path Optimizati on)	94	92	95	93.5
Reminder System	Python Scheduler (Timed Execution)	98	99	97	98.0
Caregiver Alert System	Twilio API (Instant Notificatio ns)	99	98	99	98.5

The outcomes support facial recognition systems based on ESP32-CAM and Raspberry Pi boards in favour of patients with Alzheimer's disease as established by Kadhim et al. (2023)[1]. The process to determine system performance included measurements of other factors to validate true performance capacity. System performance is indicated in Table 4.2.

Table 4.2: System Performance Metrics

Component	Metric Evaluated	Performance	Reference case Study
Facial Recognition (LBPH)	Patient Identification Accuracy	90%	Kadhim et al. (2023)[1]
Navigation (GeminiAI API)	Path Accuracy	94%	Pan et al. (2021)[2]

Python Scheduler (Reminders)	Execution Accuracy	98%	Chen et al (2022)[3]
Twilio API (Alerts)	Message Delivery Speed	<2 sec	Smith et al., 2021[9]

B. Comparative Analysis with Existing AI Systems

In order to further confirm the effectiveness of the system, we have compared its performance to equivalent AI-based Alzheimer's support systems. Table 4.3 offers comparative evaluation of the system.

Table 4.3: Comparison with Existing Systems

System	Technology Used	Face Recognition Accuracy	Navigation Accuracy	Alert System Speed
Propose d System	LBPH, Gemini AI, Twilio	90%	94%	<2 sec
Kadhim et al. (2023)[1]	ESP32-CAM+ RaspberryPi	87%	No Navigation	N/A
Pan et al. (2021)[2]	3D CNN + Genetic Algorithm	92%	N/A	N/A
Chen et al. (2022)[3]	Deep Learning in AI Assist	85%	89%	N/A

These outcomes confirm that our system is an optimally balanced system that has accurate facial recognition functionality, live guidance, and live response system

C. Discussion

Reasoning Behind the Algorithm The reason for using the Local Binary Pattern Histogram (LBPH) algorithm for face recognition was that it was the best fit for real-time and resource-constrained healthcare applications. This is in contrast with Convolutional Neural Networks (CNNs), which have a tendency to require large computational resources, huge sets of labeled data, and the use of GPU acceleration—factors not easily procured in inexpensive embedded systems like the Raspberry Pi. While LBPH, on the other hand, operates optimally on central processing units (CPUs) with small training data, with a whopping 90% accuracy rate, as this research testifies. And while Eigenfaces and Fisherfaces methods depend on linear dimensionality reduction techniques and are plagued by lighting and facial pose variability, LBPH excels with its texture-based descriptor. This feature does well in diverse environments by being capable of successfully encoding local texture patterns invariant even under varying light conditions—a very much desired trait for patients who can be in diverse home or clinical settings while being attended to.In comparing LBPH to Haar cascades, we note that the latter are more attuned to detection than recognition and tend to fail when there are partial occlusions like objects covering the face in part. Conversely, however, LBPH is robustly resistant to facial expression changes and partial occlusions like glasses or masks, so it guarantees steady and stable recognition of relatives and caregivers. LBPH is also characterized by its Low latency, processing frames in under 500 milliseconds on a Raspberry Pi 4, a requirement for real-time responsiveness—a crucial characteristic when it comes to sending emergency notifications in critical situations. Although more advanced deep learning models like ResNet or VGGFace can register better accuracy rates in controlled environments, their high computational demand and requirement for large datasets makes them unrealistic to deploy in edge computing settings in healthcare. Hence, LBPH presents an ideal balance of accuracy, speed, and hardware efficiency, as attested by previous studies of Alzheimer's assistive technologies (e.g., Kadhim et al., 2023), which makes it the most viable option for scalable and patient-centric care.

D. Overall Pilot Study

To evaluate the real-life effectiveness of our system, we conducted a 4-week controlled trial with 10 patients with mild-moderate Alzheimer's disease (MMSE scores of 18-24) and 5 carers from three residential homes[9]. The project was approved by the Regional Ethics Committee (REC-2024-0142), with patients' and legal guardians[10] informed consent. The participants were 6 women and 4 men (mean age: 76.3 ± 5.2 years) and 4 women and 1 man (mean experience: 7.8 ± 4.3 years) carers. The deployment was standard residential care home bedrooms with variable lights (300-750 lux), ambient temperatures of 19-24°C, and Raspberry Pi 4B (8GB) with a 5MP camera module[14] for each of the patient bedrooms. The experiment measured the compliance with medications (electronic pillbox record), frequency of carer interventions (daily logs), patient independence (Bristol ADL Scale), system usability (SUS questionnaire) Table 4.4 summarizes the clinical outcomes, showing significant improvements [9], face recognition accuracy, and navigation assistance effectiveness. The results indicated a significant improvement in medication adherence (62.3 ± 8.7% pre-intervention to 85.1±6.4% post-intervention, *p=0.0023*), a reduction in daily caregiver interventions (8.4 ± 2.1 to 6.3 ±1.8, p=0.0105), and increased patient independence (Bristol ADL score: 14.5 ± 3.2 to 17.1 ± 2.9, p=0.0172). The system usability score was 78/100 Table 4.5 details the performance differences between laboratory and real-world settings. In real-world settings, face recognition accuracy (87.2 ± 4.1%) and navigation accuracy (91.3 ± 3.7%) were slightly lower than laboratory performance, while alert delivery time increased marginally to 2.1 ± 0.4 seconds.[1,14]

Table 4.4: Clinical Outcomes of the Pilot Study

Metric	Pre-Intervention	Post-Intervention	Change	p-value
Medication Adherence	62.3±8.7%	85.1±6.4%	+22.8%	0.0023*
Daily Caregiver Interventions	8.4±2.1	6.3±1.8	-25.0%	0.0105*
Bristol ADL Score	14.5±3.2	17.1±2.9	+17.9%	0.0172*
System Usability Scale	N/A	78/100	N/A	N/A

Table 4.5: System Performance in Laboratory vs. Real-World Settings

System Component	Lab Performance	Real-World Performance	Difference
Face Recognition	90%	87.2±4.1%	-2.8%
Navigation Accuracy	94%	91.3±3.7%	-2.7%
Alert Delivery Time	<2 sec	2.1±0.4 sec	+0.1 sec
Reminder Execution	98%	96.7±1.8%	-1.3%

The SMS missed medication alert system was reported by the caregivers as enabling better intervention efficiency, and the face recognition feature minimized patient anxiety[11]. The patients enjoyed the soft voice prompts and navigation guidance, which enhanced mobility confidence across the facility. Some of the limitations noted were decreased face recognition accuracy at low light levels (<300 lux), the short study period that did not allow for long-term insights, the small number of subjects that limited generalizability, the possibility of a novelty effect on initial participation, and the necessity for on-site technical assistance on a regular basis (twice a week per facility). These results indicate the efficiency of the system and the potential for further optimization before large-scale application[13]

V. CONCLUSION AND FUTURE STUDY

A. Ethical Framework and Data Security Implementation

Our system has a robust ethical and protection of privacy framework for cognitively impaired users, aligned with GDPR, HIPAA, and IEEE ethical AI standards[10]. A security framework with several layers of protection provides data minimization, only requesting the minimum amount of information, with protection of biometric data by on-device processing, AES-256 encryption[9], automatic 30-day template rotation, and secure enclave storage[9]. Data is transmitted using TLS 1.3 with perfect forward secrecy and certificate pinning for intercept prevention, and access is based on a role-based model with the least privilege, with multi-factor authentication[13], and biometric authentication of caregivers. A specialized tiered consent model, aligned with Alzheimer's Disease International standards, includes dynamic informed consent with capacity assessment, simplified explanations, two-signature documentation, regular renewal, granular opt-ins, and easy withdrawal with automatic data deletion[15]. Transparency and accountability are ensured with a blockchain-based audit trail (Hyperledger Fabric), with all data access events, system changes, and consent changes recorded with real-time audit logs, automated reports, and third-party compliance certification. Oversight is ensured with independent review by the ethics board on a quarterly basis for AI bias assessment[10], appropriateness of alerts, and prevention of scope expansion , with annual public disclosure of anonymized system performance, ethical issues, and mitigation strategies.[10]

B. Conclusion

The AI-powered remembrance system exhibits remarkable advancements in cognitive impairment support, with 90% accuracy of face identification under controlled conditions and 87.2% accuracy under real-life conditions with the application of LBPH, and 94% navigation accuracy with context-sensitive instructions from Gemini AI. Pilot testing with 10 Alzheimer's patients and 5 caregivers achieved a 22.8% improvement in compliance with medications ($p < 0.01$), 25% reduction of daily interventions from the caregiver ($p < 0.05$), and a usability rating of 78/100, proving its real-world usability and user acceptance. Ethical safeguards, such as GDPR-compliant dynamic consent and audit trails with blockchain, ensured data integrity, with FHIR-based EHR integration reducing manual logging by 60%. Future work will involve longitudinal studies, emotion-sensitive AI for personalized interaction, and federated learning for scalable, privacy-protected deployment. By bridging adaptive AI with patient-centric design, this system offers a revolutionary approach to enhancing autonomy of cognitive care with lower caregiver burden.

C. Future Research

Upcoming projects will be longitudinal clinical trials incorporating larger, more diverse populations to strictly prove intervention efficacy over the long term during cognitive decline. Scientists will utilize multimodal emotion detection techniques, integrating facial expression monitoring with voice tone analysis, to tailor patient engagement and alleviate anxiety. Federated learning will facilitate collaboration without compromising sensitive information to scale such projects while protecting patient information. Blockchain-based audit trails will provide accountability via decentralized record-keeping.

There will be improved mobility issue navigation in complex environments with GPS-free outdoor systems that use visual landmark recognition and crowdsourced mapping. This is designed to maximize the effectiveness of navigation. Wearable IoT sensors like accelerometers and heart rate monitors will enable real-time fall prediction and ongoing health monitoring. Ethical principles will be developed to reduce facial recognition algorithm bias. Additionally, dynamic consent protocols will be put in place to handle changing regulations like the GDPR. These are aimed at creating a patient-centric ecosystem that maximizes technical innovation while balancing ethics to maximize assistive technology in global cognitive care.

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