Assessing the Practicality of Designing a Comprehensive Intelligent Conversation Agent to Assist in Dementia Care

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Abstract: Tools and techniques powered by artificial intelligence (AI) and its subfields like machine learning (ML) and natural language processing (NLP) have pervaded most disciplines across the global technological, economical, and sociocultural landscapes. In most areas, the permeation of AI has shown exceptional promise. Medicine and healthcare constitute a domain which has not remained aloof from the positive implications of harnessing AI. AI-driven tools, for instance in neuroimaging and health monitoring, have painted a tapestry of encouraging possibilities in this province. Such tools have found application in fields like assisting diagnosis, disease progression tracking, and patient management in many subjects within medicine. Intelligent conversation agents, more informally referred to as AI-based chatbots, form one of the most prevalent applications of AI. AI-fueled chatbots like ChatGPT have made rampant inroads into the lives of countless people around the world, easing innumerable routine tasks they are responsible for. This article offers a systematic but succinct overview of dementia, and, in this backdrop, explores the potential efficacy of a proposed intelligent conversation agent aimed at sufficing the fulfilment of the care-associated requirements of various stakeholders in dementia care. We provide an outline and a critical assessment and suggest future directions on the adoption of such a tool. We conclude that a smart conversation agent has the potential to positively overhaul the extant worldwide paradigm of dementia care.

1 INTRODUCTION

Dementia is a broad term. Instead of effectively referring to a disorder, it describes a set of symptoms that affect the general functioning of the brain. Cognitive and motor functions, inter alia, memory, reasoning, communication, and the ability to perform daily activities, including motor abilities in the later stages of the disease, are affected in dementia.

Dementia has many common embodiments. Alzheimer's disease is the most frequently occurring one, with about two-thirds of cases with dementia presenting with it. Dementia primarily affects older adults. Notwithstanding this fact, dementia is neither an inherent part of aging nor is it restricted to senescent humans. A specific disease called young-onset dementia (early-onset dementia) exists, and young-onset Alzheimer's disease is the most common form of it (Sim et al., 2022).

The World Health Organization (WHO) estimates that over 55 million people worldwide are living with dementia, and the World Alzheimer's Report, 2009, estimates that more than 65 million people will be affected by dementia by 2030 (Gulland, 2012). As the population ages, the burden of dementia is being felt not only by those diagnosed and other stakeholders active (participating) in dementia care (SDCs), but also our society.

Caring for persons with dementia (PwD) introduces plentiful challenges, most of which intensify alongside the progression of the disease. Dementia affects almost every function of the brain, from memory and cognition to motor functions and coordination. PwD may even face sensory struggles in certain cases (National Institute on Aging, 2023). The progression of dementia is commonly divided into three phases, early, middle, and late (Hol et al., 2024). In the early phase of the disease, PwD

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experience mild memory lapses and confusion. The symptoms begin with patients forgetting names and not being able to recall the task they barely arrived at a certain location for.

As the severity of the disease advances, its progression enters the second phase. PwD gradually start losing the ability to communicate, recognize loved ones, and carry out basic self-care tasks like combing their hair and brushing their teeth. Mobility issues arise in the second phase (middle stage), with shuffling, hesitation, gait apraxia and festination in gait becoming apparent (Elble, 2007). In the final stage, severe cognitive issues are seen, including far-reaching amnesia with regards to otherwise effortlessly recognizable faces and objects. Urinary incontinence and clinical-level mobility issues arise.

The Global Deterioration Scale (GDS), also known as the Reisberg Scale, is a clinical tool used to evaluate the progression of cognitive decline in PwD. This scale categorizes the disease into seven stages (Dementia Care Central, 2020). There is very slight overlap between these stages and the phases in the three-phase model. The Clinical Dementia Rating (CDR) scale is another tool to assess the severity of dementia through evaluation of cognitive and functional performance (Morris, 1993). The stages are CDR-0 (no impairment), CDR-0.5 (very mild cognitive decline), CDR-1 (mild cognitive decline), CDR-2 (moderate cognitive decline), CDR-3 (moderately severe cognitive decline), CDR-4 (severe cognitive decline), CDR-5 (very severe cognitive decline). These closely correspond to the GDS stages.

Considerations associated with such progression places immense emotional, physical, and financial strain on various SDCs, particularly the family members and caregivers (Schulz and Sherwood, 2018). They are prone to burnout due to the demanding and unrelenting nature of the care required.

Role overload is the psychological feeling – which may be real or perceived – of being left exhausted owing to the duties and demands of caregiving. Role captivity is the psychological feeling of being trapped in the role of caregiving and the resultant erosion of autonomy (Liu et al., 2019). Both phenomena have a considerable impact on the well-being of dementia caregivers affecting their mental health and quality of life (QoL).

Dementia patients face behavioural changes, such as aggression and wandering off. Caregiver stress, as explained by the model proposed by Pearlin et al., has some key factors associated with it (Pearlin et al., 1990). They include the caregiver's personal background and circumstances, including factors such as the caregiver's socioeconomic status, social support networks, and other life stressors; the demands of the role which exacerbate with the severity of the patient's illness; the strains which arise from the caregiver's other roles and responsibilities, such as family conflicts, social isolation and a lack of intermingling with friends, and financial strain (caregiving might become a full-time role, or require too much energy, leaving the caregiver with little or no chance to engage in more monetarily remunerating employment); and internal factors such as the caregiver's own personality (a caregiver may be timid by nature, or lack the energy to be an effective caregiver), perceived incompetence, and other coping mechanisms like self-pity (by convincing oneself of their role captivity) (Brodaty and Donkin, 2019).

With these factors in mind, researchers and healthcare providers enable themselves to empathize with caregivers. They are, thus, more spurred to develop useful policies to aid caregivers that mitigate the negative effects of stress on them.

The healthcare system struggles to meet the needs of dementia patients. Medical interventions are largely focused on symptom management and palliative therapeutics rather than cure (Walsh et al., 2021). In this context, caregivers, whether informal ones (Brodaty and Donkin, 2019) or hired professional aides (Ferretti et al., 2021), have become cornerstones of patient support. Informal caregivers are often seen traversing this journey with limited guidance and respite and may benefit from suitable training (Birkenhäger-Gillesse et al., 2020).

The motivation for writing this article stems from the recognition of these critical challenges and the urgent need for innovative technological solutions that can alleviate the burden on not only patients and their caregivers but also various other SDCs.

AI and NLP applications like chatbots assume the role of a promising avenue for addressing the needs of SDCs. Such tools provide aid in daily tasks and tender cognitive stimulation to PwD, mitigate social isolation by offering emotional support to those SDCs who may require it, provide information as instructed and as necessitated, as also education and edification to those freshly involved in dementia care or those already involved in dementia care but participating in some kind of transition where it behooves them to be reskilled for continued effective functioning.

However, the development of such tools requires careful consideration of not only the needs of but also the challenges faced by SDCs. Most SDCs, particularly PwD and their caregivers, face unique challenges depending on the stage of dementia, and any solution must account for these differing needs to be truly effective (Sideman et al., 2022).

2 LITERATURE REVIEW AND CURRENT APPLICATIONS

A PRISMA-guided literature review was conducted to mine publications which would help us gather knowledge regarding what has been done and what is currently happening within the domain of intelligent conversation agents being applied to facilitate and advance dementia care. The systematic screening and selection processes inherent to PRISMA left us with a total of 8 articles to be considered, out of the 126 we began with (Table 1).

T. Igarashi et al. compared the effects of human-AI interaction on the communication patterns of elderly people attending community centres and found that AI-based options can be a viable solution for routine conversational engagement with cognitively healthier elderly individuals, that is, people with early-stage dementia (Igarashi et al., 2024). F. de Arriba-Pérez et al. used a ML-based chatbot framework to dynamically predict cognitive decline (de Arriba-Pérez and García-Méndez, 2024). M. Boiting et al. have demonstrated a virtual, interned-based interaction and service framework that features an embedded chatbot which is intended to provide organized, comprehensible information to informal caregivers (Boiting et al., 2024).

C. Müller et al. drew insights from existing research and from interviews at dementia care institutions and developed a chatbot prototype to facilitate facilitates caregiver-patient interaction (Müller et al., 2022). D. Schmitz and B. Becker have presented the design of an information platform accompanied by a chatbot specializing in aiding informal caregivers (Schmitz and Becker, 2024). M. R. Lima et al. proposed leveraging an amalgamation of conversational AI and Internet of Things (IoT) to monitor older adults, specifically PwD, at home, for identification of behavioral patterns (Lima et al., 2023).

Table 1: Literature Review Table.

Author(s)	Title	Published	Brief Description of the Publication
Igarashi et al.	Detailed Analysis of Responses from Older Adults through Natural Speech: Comparison of AI vs. Humans	2024	Analyzes older adults' responses to AI vs. human interactions in dementia care.
de Arriba-Pérez & García-Méndez	Leveraging Large Language Models through NLP for Real-Time Mental Deterioration Predictions	2024	Explores using large language models and NLP for real-time predictions of mental deterioration
Boiting et al.	eDEM-CONNECT: An Ontology-Based Chatbot for Family Caregivers of People with Dementia	2024	Presents an AI chatbot integrated into the eDEM-CONNECT platform.
Schmitz & Becker	Chatbot-Mediated Learning for Caregiving Relatives of People with Dementia	2024	Investigates chatbot-mediated learning for dementia caregivers
Lima et al.	Discovering Behavioural Patterns Using Conversational Technology for In-Home Health Monitoring	2023	Introduces a cutting-edge IoT and conversational AI setup
Maia et al.	Empowering Preventive Care with GECA Chatbot	2023	Introduces the GECA chatbot for preventive care in dementia
Müller et al.	Care: A Chatbot for Dementia Care	2022	Discusses a chatbot which facilitates caregiver-patient contact
Kouroubali et al.	Developing an AI-Enabled Integrated Care Platform for Frailty	2022	Discusses building a care platform for weakness in dementia

Currently, AI applications like AI-driven serious games show a massive potential to reform dementia care. AI-fueled smart conversation agents constitute one such application. They have the potential to enhance evidence-based, personalized patient care plans (Maia et al., 2023). These chatbots can provide services like medication reminders, automated symptom tracking, and tailored event tracking and symptom monitoring support (Clark and Bailey, 2024). They can also act as virtual assistants and serve as communication bridges between dementia patients and their caregivers (Müller et al., 2022). A suitably trained chatbot can act as a virtual listening ear for PwD to express their needs and emotions while receiving companionship and emotional support (Denecke et al., 2021).

AI-driven games are associated with AI-powered chatbots and contribute to cognitive stimulation of dementia patients (Irfan et al., 2024). AI (ML) algorithms are used for early detection of cognitive decline via analysis of data from sources like historical data, electronic health records (EHR) and wearables (Graham et al., 2020). This facilitates early intervention which, in most cases, is able to arrest the pace of dementia progression. AI tools can be used for remote monitoring and continuous observation of dementia patients. This creates conducive conditions for the prompt detection of circumstance changes and administering the necessary interventions (Ahmed et al., 2020). This also obviates the need for frequent in-person visits.

3 STAKEHOLDERS IN DEMENTIA CARE

The list of SDCs begins with PwD themselves, who vary in their cognitive abilities across the stages of dementia, their caregivers, who often play a pivotal role in managing daily routines and medical appointments, healthcare providers, who must make informed decisions regarding treatment and symptom management, grassroots, voluntary, and social care organizations participating in dementia care, researchers in dementia care, physiotherapists who assist with mobility challenges faced by PwD, policymakers active in the areas of general healthcare, especially those in mental healthcare, and technologists who implement solutions based on the outcomes of researchers' activities and policymakers' guidelines.

Pharmaceutical companies, insurance companies, government agencies involved in funding dementia research and regulating care services, social workers, occupational therapists who help patients adapt to ADLs, speech-language therapists who address communication and swallowing difficulties, community organizations which provide respite care, support groups, and educational programs for caregivers as well as for PwD, technology manufacturers who focus on developing assistive technologies and devices for PwDs, advocacy groups who raise dementia awareness, nutritionists and dieticians for PwD, pharmacists who assist caregivers in managing medications for PwDs, home care providers who provide in-home assistance with daily tasks, legal advisors who help families with estate planning and guardianship (particularly in case of the families of elderly asset holders with end stage dementia), advance directives, living wills, medical power of attorney, and other legal matters and memory care specialists who deliver specialized care that is tailored to the unique cognitive needs of dementia patients, together form a host of varied stakeholders involved in dementia care, some more key to the whole enchilada of dementia care, and some comparatively less. An AI-based solution must be able to satisfy the needs of these stakeholders to be termed comprehensive and as a solution oriented towards a multi-stakeholder view (Patel et al., 2021).

To inform the development of a user-centric intelligent conversation agent in dementia care, the needs of SDCs must be enunciated with clarity. Early-stage PwD would benefit most from a chatbot, because advanced stage dementia creates hurdles for PwD (severe cognitive impairment) to efficiently utilize such technology. PwD in early stages would benefit from a chatbot that offers cognitive exercises, serious games, along with comfort, while those in advanced stages need an agent which could remind them about daily tasks, warn them not to leave their homes (for they may lose their way), and respond to simple cues. The chatbot should be designed to adapt its conversational style and complexity as dementia progresses. This would ensure that PwD feel supported without being overwhelmed and confused. This adaptability is key to maintaining engagement and promoting a sense of independence in the early stages.

Caregivers manage daily routines, medical appointments, and give emotional support to PwD. An ideal chatbot must assist a caregiver with tracking the patient's symptoms, medication adherence, and behavior management. It should provide timely reminders, alert the caregiver to any potential issues, and offer tailored advice based on the PwD's current cognitive state. The chatbot must also provide caregivers with educational and stress management resources which would help them adapt better in their role as caregivers and improve their skills.

Healthcare providers would find a chatbot that analyzes, tracks, and presents health-related data to aid informed decision-making helpful. It should also provide them with insights from the data about trends and patterns which would inform their service delivery and improve it. The AI-solution should monitor cognitive changes through the linguistic input by the patient or their caregiver, discerning their behavior patterns, and predicting any adverse happening like a reaction to a medication. The system can transmit, in real-time, the analytics to healthcare providers, who can opt for the best course of action.

Physiotherapists engaged in dementia care could need the chatbot to remind PwD to perform their prescribed exercises and monitor their progress, and also query it for help in dealing with unique situations they may not have encountered before, for example, a person with dementia revulsive to being touched. With respect to social care organizations, the AI solution should be able to connect PwD and their caregivers to local resources, such as support groups, educational programs, and respite care services. The AI system must act as a bridge between these entities and the patients they aim to help. It should be able to identify the specific needs of each patient and his or her caregiver and provide tailored recommendations. It should also facilitate access to the right resources at the right time.

The chatbot could provide researchers, technologists, policymakers, and other SDCs, inter alia pharmaceutical companies, insurance companies, thinktanks, and advocacy groups, with resources like insights and cognizant recommendations based on updated anonymized data of patients and other sources of relevant knowledge on dementia care that the underlying language model has been trained or finetuned on or has access to through techniques like Retrieval Augmented Generation (RAG), web scraping, or in-context learning (ICL). The chatbot itself should gather data relying on SDCs' interaction with it; this data pertains to, among other details, engagement levels and patient health outcomes. The insights can inform future research to improve treatment strategies, developing new medications and technologies, and designing dementia care policies and strategies, outreach and marketing plans, and so on, all of which are aimed at enhancing dementia care.

4 FULFILLING THE NEEDS OF SDCs THROUGH AN AUTOMATED CONVERSATION AGENT

Chatbots have been operative in the domain of mental health for a long time. Weizenbaum's ELIZA (1966) and Colby's PARRY (1972) were the earliest chatbots in this field which were exclusively or primarily based on rule-based models, that is, they were preliminary models which relied on predefined scripts (Saxena, 2024a, 2024b). There are several types of chatbots that have evolved since then. The types of chatbots include text-based, speech-based, and multimodal systems. Text-based chatbots, like Bard, interact through written text. Speech-based chatbots, like Alexa and Siri, interact using speech. Multimodal Chatbots, like Gemini, interact through multiple modes including text and speech, and can analyze images, audio, video, tabulated data etc. to provide insights to the user. Some of them can also generate data in various formats (multimodal) like computer programs, audio, video, images, and so on.

We propose the design of a comprehensive chatbot which can use novel AI techniques to maximize the fulfillment of the needs of the SDCs. The chatbot should specialize sufficiently in the domain of dementia care but not so much that it overfits and is incapable of processing unique, unseen conditions or queries, expressly those which are less directly related to dementia but have a bearing on it. To build such a chatbot, the underlying model must have access to diverse data. Exhaustive clinical datasets which exemplify the various stages of dementia, including patient profiles categorized by the stage of dementia, cognitive abilities, memory retention, speech patterns, motor functions, behavioral issues like aggression and wandering, cognitive assessment reports. and interventional paradigms and medications utilized for patients clustered based on gender, stage of dementia, age, and other criteria, along with the evaluated efficacy of the varied treatment approaches, patient outcomes, and service utilization rates, must be used.

Access to EHRs, anonymized patient data, and clinical trial data enable a chatbot to provide data analytics, real-time insights, and intervention advice. These insights will include detecting trends in cognitive function, identifying adverse reactions to medications, or predicting when interventions might be necessary. Learning from bulk longitudinal symptom progression datasets and from detailed anonymized multi-patient clinical history adequately empowers the model to recommend appropriately to SDCs. Similar comprehensive datasets on caregiver case studies, trends, patterns, analytics, and insights on caregiver stress and other aspects associated with caregivers and PwD, patient-caregiver conversation transcripts and other transcripts of informative conversations between various combinations of SDCs must also be used to train the model. Caregiver training manuals and comprehensive standardized training materials commonly used in skilling, upskilling, and reskilling various other SDCs.

A wide-ranging group of datasets consisting of dementia- and mental health-related medical and general texts, articles, chapters, and so on, existing policies on dementia care, pertinent recommendations from expert groups and advocacy groups, publications and research findings, reports and reviews on dementia, statistics associated with global, national, and local dementia care data collection and analytics efforts, industrial data to help SDCs like pharma and insurance firms, and a comprehensive description of latest developments and proposals in the field must also be used during model development.

To continually improve itself, one of the tactics that the model must utilize is to augment its knowledge base by leveraging the context as well as the prompts provided to it and the queries posed to it. The PwD's responses to prompts and frequency of interactions and inputs from caregivers provide feedback loops that would refine its interaction. To improve its comprehensiveness, the chatbot should be able to process multimodal data inputs. Multimodal models based on advanced neural networks like Gated Graph Recurrent Neural Networks (GRNNs), Convolutional Neural Networks (CNNs), RNNs, and Transformers must be trained using these multi-format datasets (Saxena and Saxena, 2024).

5 STRATEGIES THAT MUST BE APPLIED WHEN BUILDING THE SPECIALIZED CONVERSATION AGENT

Domain-specific data collection and curation is an essential tool to build specialized models. The language model must be exposed to datasets that are highly relevant to the field of dementia care as already described. The language can be pretrained on the data or can be a preexisting model finetuned on it. In this way, transfer learning and finetuning become relevant strategies where we start with an open-source LLM like Mistral or BERT, which has already been pretrained on large volumes of general language data. This model is then finetuned on domain-specific data related to dementia care to inform an efficient chatbot. Finetuning allows the model to specialize by focusing on labeled data. The process adjusts the model's internal weights so that it aligns with dementia-specific requirements.

Prompt engineering can be applied to not only the already rendered specialized chatbot for more efficient responses but also to general-purpose language models to adapt them for specific SDC needs without retraining the entire model. Prompt engineering involves users themselves, who must carefully craft queries and frame – with explicitness, straightforwardness, and elaboration – such problems which will be served as prompts to the chatbot. This helps an agent generate highly meaningful outputs which show exceeding appropriateness to the user's needs.

Incorporating external knowledge bases also offers a competent enhancement to the model. Integrating healthcare ontologies like ICD-10 (Cooke et al., 2011), dementia-specific databases like International Alzheimer's Disease Research Portfolio (IADRP) (Liggins et al., 2014), clinical care guidelines (Shaji et al., 2018), evidence-based care guidelines, multi-omics data and so on, associated with dementia (Saxena et al., 2023), ensures accuracy and holism in the chatbot's responses.

Constructing knowledge graphs to represent the relationships between various concepts and words that a model is supposed to learn is another way to train a model of surpassing systematicness. Using specialized tokenization and vocabulary will help the chatbot accurately interpret dementia-associated medical abbreviations and jargon (such as PwD). Task-specific training objectives enable the model to focus on specific outcomes important to SDCs (Li et al., 2020).

Custom loss functions can train an efficient dementia care model. Active learning and human-in-the-loop feedback are strategies where experts periodically review an ML model's output and provide constructive feedback which is then used by technologists to improve the model's performance over time.

To keep up with the most updated information relevant to dementia care and to be resilient to the evolving nature of the arena, incorporating continual learning is essential (Wang et al., 2023). Leveraging RAG is vital in scenarios where real-time, accurate information is required. A model with the ability to scrap the web for up-to-the-minute dementia research, clinical advances, recommendations, policy, and technology ensures that newly available pertinent information can be accessed and processed as well as integrated into the conversational agent's responses.

6 DISCUSSION AND CHALLENGES

Decision support should be a major aspect of the chatbot. Systems which offer decision support are termed clinical decision support systems (CDSSs) (Bruun et al., 2019). To accelerate the implementation of anticipatory approaches while strengthening multimodal and inclusive care for seniors, shared care planning smoothens communication between various SDCs. A multimodal AI model for an efficient paradigm of dementia care must also incorporate diagnostic pathology algorithms applicable to dementia, including computer vision DL algorithms that enable it to analyze pathological images like MRIs (Saxena et al., 2019). This augments CDSSs and gives the underlying model diagnostic capabilities.

A chatbot is an obvious example of the rapidly burgeoning field of human-machine interaction (human-computer interaction) (Saxena et al., 2023b). A major concern in developing a chatbot that is useful to a broad variety of stakeholders is creating a user-centric design with a user-friendly interface (Saxena et al., 2024). Considering the cognitive impairments associated with dementia, it must be even more intuitive, facile to navigate, and adaptable to the varying abilities of its users.

A significant challenge that arises in case of a complex ML model is its potential lack of interpretability and explainability. It is vital for various SDCs to have at least some understanding regarding how the chatbot arrives at its recommendations. Clear explanations help build trust in the system. Ambiguous decisions cause confusion and may result in misuse of an AI-based system. Explainable AI techniques (XAI) like LIME and SHAP should be applied.

Patient data privacy is one of the paramount concerns in the realm where AI and any aspect of healthcare or society in general intersect. Ensuring the anonymity and confidentiality of patient data is essential to comply with regulations like Health Insurance Portability and Accountability Act (HIPAA) and General Data Protection Regulation (GDPR).

The right data is crucial for any ML model to be trained or finetuned well. So, data availability is another challenge to consider. In the case of a comprehensive chatbot in dementia care, there is no scope for a hallucinatory response to any query, (hallucination implies the generation of incorrect and nonsensical responses for queries that the chatbot or the model is unable to, despite an extensive search through its vector databases, find a germane answer to), for misleading and inaccurate outputs may lead to harmful decisions by SDCs, and may even endanger lives.

The chatbot must be constantly and efficiently connected to emergency response services and healthcare providers. The system must be capable of expeditiously propagating any warning to emergency response teams and healthcare professionals in case PwD encounter any crisis.

7 FUTURE DIRECTIONS AND CONCLUSION

Dementia is a significant global health issue. The WHO (2003) reports that dementia accounts for 11.2% of years lived with disability in individuals past 60 years of age. Dementia has been able to surpass the impact of global impact of stroke, cardiovascular disease, and cancer. Advances in AI over the past few years have demonstrated great potential for enhancing dementia care and management.

In this context, The AI-driven intelligent conversation agent we propose shows promise to portray the capability to significantly alleviate the dementia-associated emotional, physical, and financial burdens that fall on the shoulders of different SDCs.

However, it must be taken care that such a chatbot is designed to become progressively better at accommodating the diverse and evolving needs of PwD and other SDCs. Simplicity, accessibility, and adaptability must also be ensured. Efficient collaboration between various SDCs can lead to the development of an effective intelligent conversation agent in dementia care and the resolution of any roadblocks in its implementation and deployment. Further future directions include the possible releasing of the agent as freeware in the best interests of the society, ensuring continued funding for incremental enhancements in its performance, and building similar across-the-board systems for other disciplines in the field of medicine as well as in other spheres.

REFERENCES

Sim, J., Li, H., Hameed, S., & Ting, S. K. S. (2022). Clinical Manifestations of Early-Onset Dementia With Lewy Bodies Compared With Late-Onset Dementia With Lewy Bodies and Early-Onset Alzheimer Disease. JAMA Neurology. https://doi.org/10.1001/jamaneurol.2022.1133.

Gulland, A. (2012). Number of people with dementia will reach 65.7 million by 2030, says report. BMJ, 344, e2604–e2604. https://doi.org/10.1136/bmj.e2604.

National Institute on Aging. (2023). Take care of your senses: The science behind sensory loss and dementia risk. National Institute on Aging. https://www.nia.nih.gov/news/take-care-your-senses-science-behind-sensory-loss-and-dementia-risk.

Hol, E., Van Noort, O., Schotanus, F., & Van Montfort, G. (2024). Definition and design of client profiles for dementia clients in the Dutch home care sector. Retrieved from https://essay.utwente.nl/65895/1/Hol_MA_MB.pdf.

Elble, R. J. (2007). Gait and dementia: moving beyond the notion of gait apraxia. Journal of Neural Transmission, 114(10), 1253–1258. https://doi.org/10.1007/s00702-007-0743-3.

Dementia Care Central. (2020). Seven Stages of Dementia | Symptoms, Progression & Durations. Dementiacarecentral.com. https://www.dementiacarecentral.com/aboutdementia/facts/stages/.

Morris, J. C. (1993). The Clinical Dementia Rating (CDR): Current version and scoring rules. Neurology, 43(11), 2412. https://doi.org/10.1212/wnl.43.11.2412-a.

Schulz, R., & Sherwood, P. R. (2018). Physical and mental health effects of family caregiving. AJN, American Journal of Nursing, 108(Supplement), 23–27. https://doi.org/10.1097/01.naj.0000336406.45248.4c.

Liu, Y., Dokos, M., Fauth, E. B., Lee, Y. G., & Zarit, S. H. (2019). Financial Strain, Employment, and Role Captivity and Overload Over Time Among Dementia Family Caregivers. The Gerontologist, 59(5). https://doi.org/10.1093/geront/gnz099.

Pearlin, L. I., Mullan, J. T., Semple, S. J., & Skaff, M. M. (1990). Caregiving and the Stress Process: An Overview of Concepts and Their Measures. The Gerontologist, 30(5), 583–594. https://doi.org/10.1093/geront/30.5.583.

Brodaty, H., & Donkin, M. (2019). Family Caregivers of People with Dementia. Dialogues in Clinical Neuroscience, 11(2), 217–228. https://doi.org/10.31887/DCNS.2009.11.2/hbrodaty.

Walsh, S. C., et al. (2021). Palliative care interventions in advanced dementia. Cochrane Database of Systematic Reviews, 2021(9). https://doi.org/10.1002/14651858.cd011513.pub3.

Ferretti, C., Nitrini, R., & Brucki, S. M. D. (2021). Virtual Support in Dementia: A Possible Viable Strategy for Caregivers. Frontiers in Neurology, 12. https://doi.org/10.3389/fneur.2021.662253.

Birkenhäger-Gillesse, E. G., Achterberg, W. P., Janus, S. I. M., Kollen, B. J., & Zuidema, S. U. (2020). Effects of caregiver dementia training in caregiver-patient dyads: A randomized controlled study. International Journal of Geriatric Psychiatry. https://doi.org/10.1002/gps.5378.

Sideman, A. B., et al. (2022). Facilitators and Barriers to Dementia Assessment and Diagnosis: Perspectives From Dementia Experts Within a Global Health Context. Frontiers in Neurology, 13, 769360. https://doi.org/10.3389/fneur.2022.769360.

Igarashi, T., Iijima, K., Nitta, K., & Chen, Y. (2024). Detailed Analysis of Responses from Older Adults through Natural Speech: Comparison of Questions by AI Agents and Humans. International Journal of Environmental Research and Public Health, 21(9), 1170. https://doi.org/10.3390/ijerph21091170.

de Arriba-Pérez, F., & García-Méndez, S. (2024). Leveraging large language models through natural language processing to provide interpretable machine learning predictions of mental deterioration in real time. Arabian Journal for Science and Engineering. https://doi.org/10.1007/s13369-024-09508-2.

Boiting, M., et al. (2024). eDEM-CONNECT: An Ontology-Based Chatbot for Family Caregivers of People with Dementia. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, 73–91. https://doi.org/10.1007/978-3-031-60665-6_6.

Müller, C., Paluch, R., & Ali, H. A. (2022). Care: A chatbot for dementia care. Dl.gi.de, 10.18420/muc2022-mci-src-442. Retrieved from https://dl.gi.de/items/00956d93-3952-4fa3-a2e2-ffe817934a16.

Schmitz, D., & Becker, B. (2024). Chatbot-Mediated Learning For Caregiving Relatives of People With Dementia: Empirical Findings and Didactical Implications For Mulitprofessional Health Care. Journal of Multidisciplinary Healthcare, 17, 219–228. https://doi.org/10.2147/jmdh.s424790.

Lima, M. R., et al. (2023). Discovering Behavioural Patterns Using Conversational Technology for in-Home Health and Well-being Monitoring. IEEE Internet of Things Journal, 10(21), 18537–18552. https://doi.org/10.1109/jiot.2023.3290833.

Maia, E., Vieira, P., & Praça, I. (2023). Empowering Preventive Care with GECA Chatbot. Healthcare, 11(18), 2532. https://doi.org/10.3390/healthcare11182532.

Clark, M., & Bailey, S. (2024). Chatbots in Health Care: Connecting Patients to Information: Emerging Health Technologies. Ottawa (ON): Canadian Agency for Drugs and Technologies in Health. Retrieved from https://www.ncbi.nlm.nih.gov/books/NBK602381/.

Denecke, K., Abd-Alrazaq, A., & Househ, M. (2021). Artificial Intelligence for Chatbots in Mental Health: Opportunities and Challenges. In Multiple Perspectives on Artificial Intelligence in Healthcare (pp. 115–128). https://doi.org/10.1007/978-3-030-67303-1_10.

Irfan, B., Kuoppamäki, S., & Skantze, G. (2024). Recommendations for designing conversational companion robots with older adults through foundation models. Frontiers in Robotics and AI, 11, 1363713. https://doi.org/10.3389/frobt.2024.1363713.

Graham, S. A., et al. (2020). Artificial intelligence approaches to predicting and detecting cognitive decline in older adults: A conceptual review. Psychiatry Research, 284, 112732. https://doi.org/10.1016/j.psychres.2019.112732.

Ahmed, Z., Mohamed, K., Zeeshan, S., & Dong, X. (2020). Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. Database, 2020. https://doi.org/10.1093/database/baaa010.

Patel, N. K., et al. (2021). Engaging multi-stakeholder perspectives to identify dementia care research priorities. Journal of Patient-Reported Outcomes, 5(1). https://doi.org/10.1186/s41687-021-00325-x.

Saxena, R. R. (2024a). Examining Reactions about COVID-19 Vaccines: A Systematic Review of Studies Utilizing Deep Learning for Sentiment Analysis. Authorea Preprints, Techrxiv. https://doi.org/10.36227/techrxiv.171262869.98334885/v1.

Saxena, R. R. (2024b). Beyond Flashcards: Designing an Intelligent Assistant for USMLE Mastery and Virtual Tutoring in Medical Education (A Study on Harnessing Chatbot Technology for Personalized Step 1 Prep). arXiv.org. https://arxiv.org/abs/2409.10540..

Saxena, R. R., & Saxena, R. (2024). Applying Graph Neural Networks in Pharmacology. Authorea Preprints, Techrxiv. https://doi.org/10.36227/techrxiv.170906927.71541956/v2.

Cooke, D. T., Gelfand, G. A. J., & Broghammer, J. A. (2011). Billing, Coding, and Credentialing in the Thoracic Surgery Practice. Thoracic Surgery Clinics, 21(3), 349–358. https://doi.org/10.1016/j.thorsurg.2011.04.003.

Liggins, C., et al. (2014). International Alzheimer's Disease Research Portfolio (IADRP) aims to capture global Alzheimer's disease research funding. Alzheimer's & Dementia, 10(3), 405–408. https://doi.org/10.1016/j.jalz.2013.12.013.

Shaji, K. S., Sivakumar, P. T., Rao, G. P., & Paul, N. (2018). Clinical Practice Guidelines for Management of Dementia. Indian Journal of Psychiatry, 60(Suppl 3), S312–S328. https://doi.org/10.4103/0019-5545.224472.

Saxena, R., Carnevale, K., Yakymovych, O., Salzle, M., Sharma, K., & Saxena, R. R. (2023a). Precision, Personalization, and Progress: Traditional and Adaptive Assessment in Undergraduate Medical Education. Innovative Research Thoughts, 9(4), 216–223. https://doi.org/10.36676/irt.2023-v9i4-029.

Li, J., Zhang, Z., & Zhao, H. (2020). Dialogue-adaptive Language Model Pre-training From Quality Estimation. arXiv.org. Retrieved from https://arxiv.org/abs/2009.04984.

Wang, L., Zhang, X., Su, H., & Zhu, J. (2023, June 10). A Comprehensive Survey of Continual Learning: Theory, Method and Application. arXiv.org. https://arxiv.org/abs/2302.00487.

Bruun, M., et al. (2019). Impact of a Clinical Decision Support Tool on Dementia Diagnostics in Memory Clinics: The PredictND Validation Study. Current Alzheimer Research, 16(2), 91–101. https://doi.org/10.2174/1567205016666190103152425.

Saxena, R., Carnevale, K., Saxena, R. R., Moyer, C., Sahota, N., Gillett, R. L., & Saxena, A. R. (2019). Thinking, Creating, Innovating: Utilizing Algorithms in PBL Setup to Enhance Pathology Education. American Journal of Clinical Pathology, 152(Supplement_1), S100–S100. https://doi.org/10.1093/ajcp/aqz119.003.

Saxena, R. R., Nelavala, S. S., & Saxena, R. (2023b). MuscleDrive – Electromyographic Navigation of a Four-wheeled Remote-Operated Vehicle: A Novel Proof of Concept Based on End-to-End Software Integration. FMDB Transactions on Sustainable Health Science Letters, 1(2), 107–117. Retrieved from https://www.fmdbpub.com/uploads/articles/170340553189494.%20FTSHSL-70-2023.pdf.

Saxena, R. R., Voss, W., & Mahmood, S. (2024). Empowering Learners Globally: A User Interface and User Experience Design Case Study Describing the Development of a Mobile Application That Bridges the Educational Divide Through Accessible Instructional Resources. Authorea Preprints, Techrxiv. https://doi.org/10.36227/techrxiv.172175659.90097054/v2.