CogVis: A Human-Centred Interface for High-Dimensional Alzheimer's Disease Data

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Abstract. Large, multimodal longitudinal studies like the Alzheimer's Disease Neuroimaging Initiative (ADNI) are rich in clinical data but highly complex for clinicians and researchers to navigate. While pioneering explainable AI (XAI) models are emerging to successfully predict cognitive decline, there remains a need for domain experts to visually examine the fragmented, high-dimensional data that forms the basis for the algorithmic predictions. We introduce CogVis, a novel visual analytics platform designed to explore Alzheimer's Disease progression, identify state conversions (e.g., from Mild Cognitive Impairment to Alzheimer's Disease), and visually compare individual patient trajectories against cohort distributions. By providing an initial overview followed by patient-level filtering within a broader cohort context, CogVis bridges the gap between raw longitudinal data and clinical interpretability, serving as a human-centred framework for navigating complex dementia-related datasets. A video overview of our research prototype is available at this link.

Keywords: Visual Analytics · Longitudinal Data · Alzheimer's Disease · Patient-Cohort Comparison · Explainable AI.

1 Introduction and Motivation

Dementia is a global health challenge requiring early detection through the analysis of demographic, cognitive, and biological data. To address this challenge, researchers frequently utilise the Alzheimer's Disease Neuroimaging Initiative (ADNI) database, which provides one of the largest multimodal longitudinal cohorts worldwide, tracking over 3,000 patients with repeated imaging, biomarker, genetic, and cognitive assessments for more than 20 years. While recent breakthroughs in interpretable machine learning (ML) are successfully utilising these datasets to create generalisable prognostic models, a critical problem remains: experienced clinicians and researchers struggle to synthesise the fragmented, high-dimensional patient data upon which these models are trained. To explore how transparent visual analytics can transform complex datasets into clinical insights, this paper presents a research prototype called CogVis.

2 Related Work

A scoping review by Xia et al. [14] shows that predicting individual conversion from Mild Cognitive Impairment (MCI) to Alzheimer's Disease (AD) dementia is the primary objective in multimodal ML literature, relying on variations of imaging, genetic, and neuropsychological indicators [3], which we adopted in our visualisations, along with: classifying stages of AD [9] and prediction of decline in cognitive test scores [6].

While the models achieved accuracy in research settings, they possess clinical limitations. As Xia et al. indicates, only 10.1% of the papers in their review were tested in clinical settings. Therefore, traditionally, purely ML approaches (1) lack clinical trust due to their black box nature, (2) provide contextual fragmentation of predictions, and (3) exclude patients and carers.

A pioneering exception is the Predictive Prognostic Model (PPM), which utilises a transparent framework validated across real-world memory clinics to predict individualised trajectories of cognitive decline [4]. However, even when models like the PPM provide algorithmic transparency, healthcare professionals face a significant data-navigation challenge. Clinicians are often limited by time and resources, making it difficult to navigate the fragmented, high-dimensional patient data [12,13] used to train these models.

Existing Alzheimer's disease data exploration and visualisation portals are not numerous and often prioritise specialised research functions over point-of-care clinical usability. For instance, platforms such as ADAS-viewer focus heavily on the complex, integrative analysis of multi-omics and genetic data for molecular biomarker discovery [1], while others function primarily as repositories for bulk database retrieval [7]. Furthermore, while recent visual XAI platforms provide excellent diagnostic transparency for single MRI scans [2], these tools highly valuable for deep biological research lack the longitudinal, interactive patient-cohort comparisons [8] and patient-centric design [5,11] required by healthcare professionals to track disease progression over time in clinical settings.

Thus, the eventual aim of CogVis is to make complex datasets and cohort distributions highly interpretable by clinicians and accessible by the patients and carers. By (a) delivering an accessible, interactive overview of the ADNI dataset supplemented by filtering, selection and details-on-demand for anonymised patient trajectories, CogVis allows domain experts to visually examine the data that underpins AI predictions. Furthermore, (b) by iteratively co-producing the interface with a neurologist and public stakeholders to ensure educational utility, CogVis equips clinicians with a humanised, visual framework to ultimately translate these complex, high-dimensional datasets into empathetic communication aids for patients.

3 Methodology and Visualisation Prototype

To ensure clinical validity and public accessibility, CogVis is being iteratively co-produced with a neurologist and through two Patient and Public Involvement and Engagement (PPIE) sessions. The neurologist provides domain expertise, such as translating biomarker significance and strategically framing the tool to assess individual AD conversion risk against cohort distributions. Concurrently, PPIE stakeholders evaluated early mockups (Fig. 1,2). While they validated the platform's educational utility, their feedback informs us of further accessibility enhancements, such as adopting colour-blind-friendly palettes and integrating visual iconography to simplify complex medical data.

Following Shneiderman's "overview first, zoom and filter, then details-on-demand" visualisation paradigm [10], the platform employs a dual-view architecture engineered via Tableau and Python (Matplotlib, Streamlit, Plotly). The overview entry point is a **Treemap** that visually distils over 3,000 patients into nested, clickable hierarchies (visit count → age group → gender). This enables users to filter and isolate clinical cohorts they are interested in exploring.

Selected cohorts populate a longitudinal **Heatmap**. Columns represent demographic details and key markers, while grouped rows encode anonymised patient trajectories over time, with the height of grouped rows indicating visit frequency. All the key markers, except some demographic data and reference values, are mapped to a green-red colour scale, where red denotes pathological AD progression and green indicates healthy baselines, helping instant visual pattern recognition. To refine the view further, a dedicated control panel enables filtering by specific disease trajectories (e.g., strictly isolating patients who converted from Cognitively Normal to Alzheimer's Disease) and querying across biomarker thresholds. Details-on-demand can be retrieved via interactive tooltips. A video overview of the prototype is available at this link.

4 Conclusion and Future Work

The CogVis visualisation tool is a work-in-progress prototype addressing ADNI dataset complexity to facilitate comprehension by domain experts and the public. Ongoing development includes several planned enhancements to refine the platform's accessibility and clinical utility. To ensure a patient-centric interface, two additional PPIE sessions will iteratively improve the design. Technically, the visual architecture will be upgraded to feature a side-by-side treemap and heatmap view for improved data comparison, alongside customisable treemap hierarchies allowing users to track specific disease trajectories, such as the transition from MCI to AD. Finally, to validate practical effectiveness, the updated platform will undergo a formal usability review by clinical domain experts. Beyond this pilot study, the work can be extended by adapting the codebase for other AD datasets, such as OASIS or AIBL, and by integrating advanced dimensionality reduction algorithms, such as t-SNE and UMAP, alongside Generative AI as an additional layer of CogVis to enhance record comprehensiveness.

5 Acknowledgments

This research is funded by the SEED grant from the University of Nottingham.

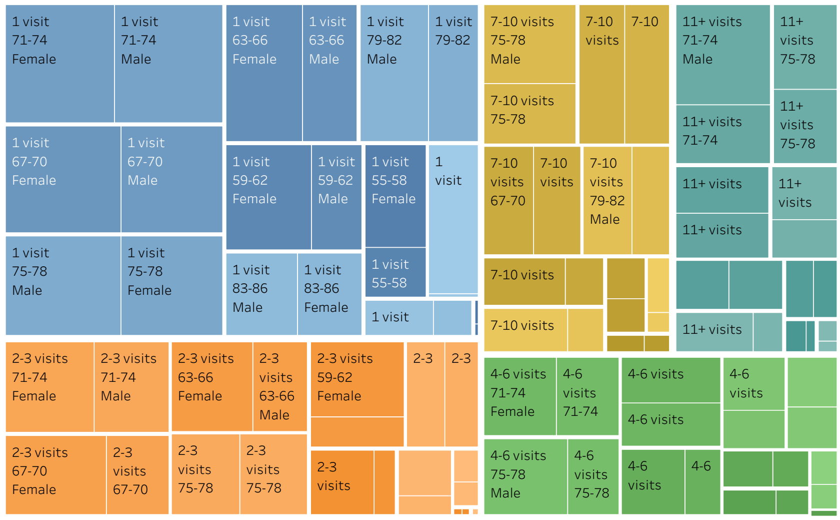

Fig. 1. Treemap visualising all the patients in the ADNI dataset grouped by visit counts, age ranges, and gender profiles. An interactive version is available here.

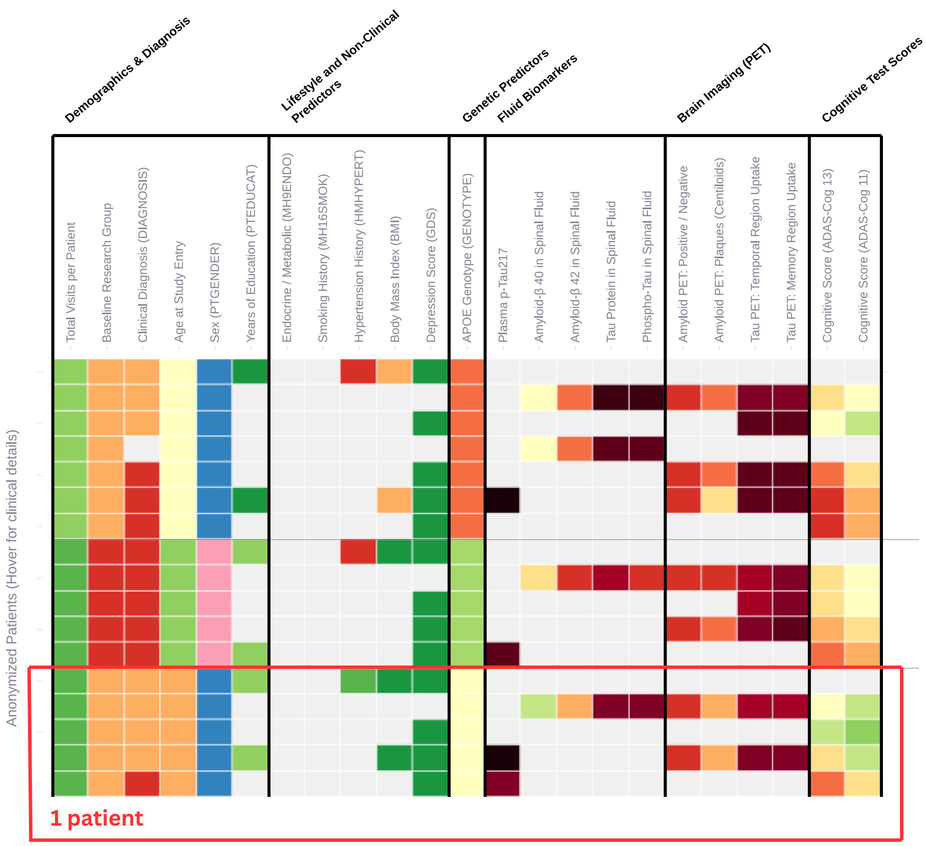

Fig. 2. Heatmap mapping details about each patient for each visit. The colour legend is available here.

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