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BIOMARKERS

POSTER PRESENTATION

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BIOMARKERS (NON-NEUROIMAGING)

Developing an AI algorithm to detect predictors of poor performance in a self-administered, web-based digital biomarker for Alzheimer's Disease: proof of concept

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Abstract

Background: The Visual Short Term Memory Binding (VSTMBT) task is a gold-standard cognitive assessment for the identification of Alzheimer's Disease and associated risk factors, including during the preclinical stage. Previous work from our group (Butler, Watermeyer, …& Parra 2024) demonstrated in a small number (n=37) of healthy older adults that data collected using a web-based, self-administrated version of the task provides data comparable to that collected in laboratory conditions. Here we incorporated a machine learning (ML) approach to explore impacts of risk factors on this task in a larger digital dataset.

Method: Using data (n=359) collected from an online study incorporating the VSTMBT and lifestyle, psychological, and health data, we created a Binding Cost score which has shown to approximate AD-related neuropathology (Parra et al., 2024). This categorised participants as either strong-binders (SB – indicative of no pathology; 85.9% percent of the sample) or weak-binders (WB – indicative of pathology; 14.1%). We trained three ML algorithms (Random Forest (RF), K-Nearest Neighbour (KNN) and Decision Tree (DT) by employing SMOTE technique to overcome the imbalance in group distribution. We applied a 10-fold cross-validation with hyper-parameter tuning to optimise the models based on the selected variables (including age, sex, education, BMI, loneliness, and existing-morbidities) to predict individual's risk of cognitive impairment based on the groupings (SB vs WB). Models' performances were examined on 20% of unseen test set.

Result: Aside from existing morbidities, which were higher in weak binders (WB = 0.41 (sd+2=0.79); SB =0.22(sd+2=0.49); t=2.21; p=0.03), other measures did not differ between groups. Regarding performance of the ML models, RF achieved the best

performance (accuracy: 91%; recall=91%; precision=91%; AUC=97%) compared to KNN (accuracy: 81%; recall=81%; precision=84%; AUC=91%) and DT (accuracy: 81%; recall=81%; precision=82%; AUC= 85%). Feature importance analysis of the RF model suggests mental health, BMI, and fatigue have the highest impact on the prediction model, while sex and multi-morbidity score have the least impact.

Conclusion: The study underscores the potential of web-based cognitive assessments and ML for remote monitoring and early identification of AD risk factors, contributing to the advancement of accessible tools for early detection.