AI-Driven Prognosis of Dementia: Risk Stratification From Baseline Clinical Profiles in a Large Longitudinal Cohort

Kim, Claire (School: Lamar Academy)

Dementia affects more than 55 million people worldwide, and its prevalence is projected to nearly triple by 2050. A major clinical challenge is identifying individuals who are likely to experience cognitive decline while they still appear cognitively normal. Current prediction approaches often rely on expensive biomarkers or neuroimaging, or provide only population-level risk estimates rather than individualized short-term prognosis. This study investigates whether a small set of routinely collected baseline clinical variables can generate accurate predictions of near-term dementia conversion. Cognitively normal individuals at baseline (CDR = 0) were selected and evaluated for dementia progression within 2-, 3-, and 5-year windows. A MLP model was trained using five clinically feasible features: age, sex, education, APOE e4 status, and MMSE score. Predicted probabilities were converted into clinically interpretable risk tiers (low, intermediate, and high) using thresholds derived from training data. Across all prediction horizons, the models demonstrated stable discrimination and good calibration between predicted and observed dementia incidence. Risk stratification further revealed monotonic increases in observed dementia progression from low- to high-risk groups, confirming the clinical interpretability of the predictions. These results demonstrate that a small, clinically feasible set of baseline variables can generate accurate, individualized predictions of dementia conversion within 2–5 years. By translating routine clinical data into actionable risk categories, this framework supports scalable, AI-driven dementia prognosis and may help inform monitoring strategies and preventive interventions.

Awards Won: