EARLY DETECTION OF ALZHEIMER'S DISEASE USING DIGITAL BIOMARKERS: INSIGHTS FROM THE PROVIDEMUS alz PROJECT

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AIMS

Alzheimer's disease (AD) is the leading cause of dementia globally (60%–80% of cases) [1].
Early screening is challenging, but subtle cognitive and behavioral changes can indicate impending impairment.
This is a feasibility study on developing a **passive, ubiquitous assessment of cognitive performance fluctuations** over time
This research explores the potential of **consumer-grade portable and wearable devices** to measure behavioral changes linked to cognitive performance variations in cognitively healthy individuals.
This poster presents the **predicability of daily cognitive performance fluctuations**, using only passively and ubiquitously collected TechROs data.

COHORT

Eighty-two cognitively healthy volunteers living in **Switzerland** and/or **France**.
Twenty (24%) have/had cases of dementia in the family.

Age: between 46 and 78, mean 58.024 (±8.739) years.
Sex at birth: 48 (59%) Female, 34 (41%) Male, and 0 Intersex.
Self-identified race: 76 (93%) White, 2 (2%) Latino, 2 Asian, and 2 undisclosed.
Education years: between 6 and 40, mean of 17.936 (±5.218).
Body mass index: between 18 and 41, mean of 24.730 (±4.260).

METHODS

Data was collected **between 10 March and 21 October 2024 (225 days)**.

Samples were generated **between two active data points** separated by at least 30 days, combined with all the available passive data from active point 1 to point 2.
For each sample:
- **Active data** is represented as the absolute difference between points 1 and 2.
- **Passive data** is represented with one of five possible derived features (across the sample): mean (M), median (Mdn), SD, coefficient of variation (CV), and amplitude (Amp).

Compared modeling with multiple linear regression, ridge regression, k-nearest neighbors (KNN), random forest (RF), and extreme gradient boosting (XGB).
Passive data **features** were **selected per model and active data type** according to their highest absolute feature importance (ratio).

The final results were obtained using the optimized selected features, controlling for age, diet, sex, body mass index, cognitive reserve, digital literacy, subjective age, percentage of missing data in the sample, sample size, timezone changes, and watch-wearing habits.
We have standardized active and passive data values.

THE DATA POINTS

CHARACTERISTICS OF THE INDIVIDUAL

PRO	**Cognitive reserve***
PRO	**Demographics***
PRO	**Medical history***

CHARACTERISTICS OF THE ENVIRONMENT

TechRO	**Season***
TechRO	**Weather***
TechRO	**Air quality***
TechRO	**Relative location***

SYMPTOM STATUS

PRO	**Depression****
PRO	**Dysphoria****
PRO	**Neuroticism****
PRO	**Anxiety****
PRO	**Stress****

PerfRO Performance-reported outcome
PRO Patient-reported outcome
TechRO Technology-reported outcome

BIOLOGICAL, PHYSIOLOGICAL VARIABLES

TechRO	**Heart rate levels while exercising***
TechRO	**Sleep fragmentation***
TechRO	**Sleep-wake cycle disturbances***
TechRO	**Sleeping and resting heart rate***

FUNCTIONAL STATUS

TechRO	**Diurnal napping***
TechRO	**Nocturnal sleep duration***
TechRO	**Physical activity levels***
TechRO	**Gait speed, variability***
TechRO	**Step length, width, height, time***
TechRO	**Swing properties***
PRO	**Affect****
PerfRO	**Attention control****
PerfRO	**Activity shifting****
PerfRO	**Motor actions****
PerfRO	**Processing speed****
PerfRO and PRO	**Memory****

* Data for model creation
** Data for validation

Outcomes being collected, following the Wilson and Cleary [2] model

DATA COLLECTION TOOLS

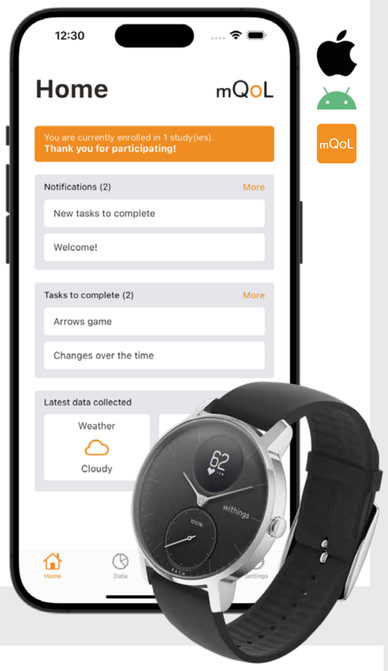
Observational study of **2 years** in English, French, and Portuguese.

Collection of **active and passive data** between March 2024 and April 2026.

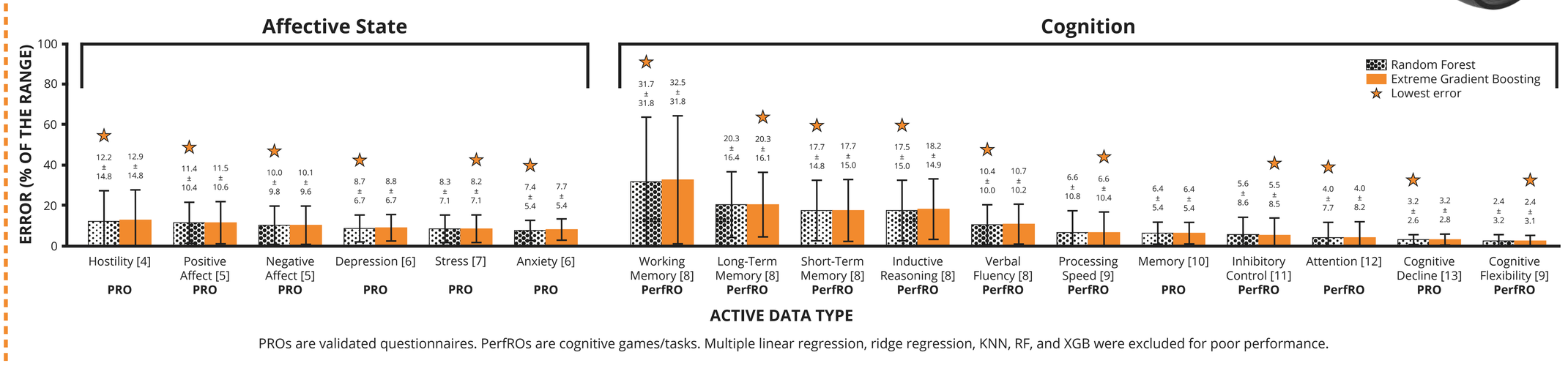
Using a **mobile application** (the mQoL Lab [3]) and a **clinically tested smartwatch** (Withings Steel HR).

PROs and PerfROs are collected every three months using the mQoL app.
TechROs continuously using the app and the smartwatch.

Protocol: bit.ly/Providemus2024Protocol



RESULTS



PROs are validated questionnaires. PerfROs are cognitive games/tasks. Multiple linear regression, ridge regression, KNN, RF, and XGB were excluded for poor performance.

ACTIVE DATA TYPE	PASSIVE FEATURE (top 3)	IMPORTANCE
Anxiety (RF)	Wake-up duration (M)	7.3%
	Wakefulness after sleep onset (M)	6.8%
	Sleep latency (CV)	6.4%
Stress (XGB)	Sleep minimum heart rate (CV)	10.6%
	Caloric expenditure (Mdn)	8.9%
	24-hours max. heart rate (CV)	8.0%
Cognitive Flexibility (XGB)	Sleep maximum heart rate (CV)	11.9%
	Caloric expenditure (Mdn)	10.1%
	Sleep minimum heart rate (M)	9.7%
Cognitive Decline (RF)	Wake-up duration (CV)	7.0%
	Caloric expenditure (Amp)	6.9%
	Wakefulness after sleep onset (Amp)	6.2%

CONCLUSIONS

Although still with a **limited amount of data**, the results showed the **accurate prediction** of active measurements using only passive and ubiquitously collected data. Memory poses the most significant challenges, probably linked to the complexity of its mechanism.
These **results confirm** the possibility of **constant and effortless measurement of cognitive performance and affective state** across the lifespan.
Future research should **focus on using the complete time series of data** instead of derived features.

More info and **other publications** at **PROVIDEMUS.UNIGE.CH**.

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