

AI-Powered Remote Multimodal Digital Platform for Early Detection and Longitudinal Monitoring of Neurocognitive Disorders (MonitorCog-AI)

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Background

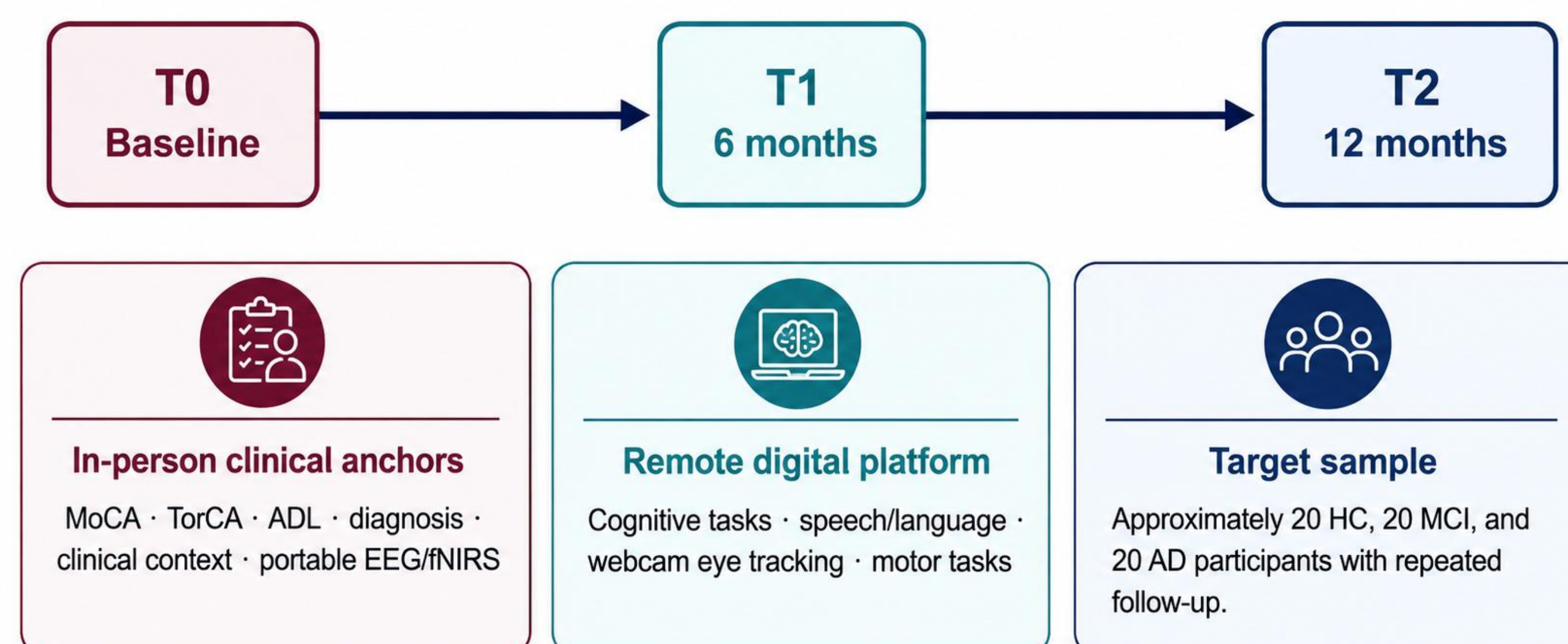
- ❖ Alzheimer's disease (AD) creates a growing clinical and societal burden, making timely detection and repeated monitoring increasingly important.
- ❖ The MCI stage is a critical window for earlier diagnosis, care planning, and potential disease-modifying intervention.
- ❖ Conventional assessment pathways are resource-intensive, episodic, and limited by specialist access and wait times.
- ❖ AD affects multiple domains beyond cognition, including speech/language, eye movements, and fine motor function.
- ❖ Most digital tools remain single-domain or hardware-dependent, motivating a scalable, remote, AI-enabled multimodal platform for detection and longitudinal monitoring.

Methods

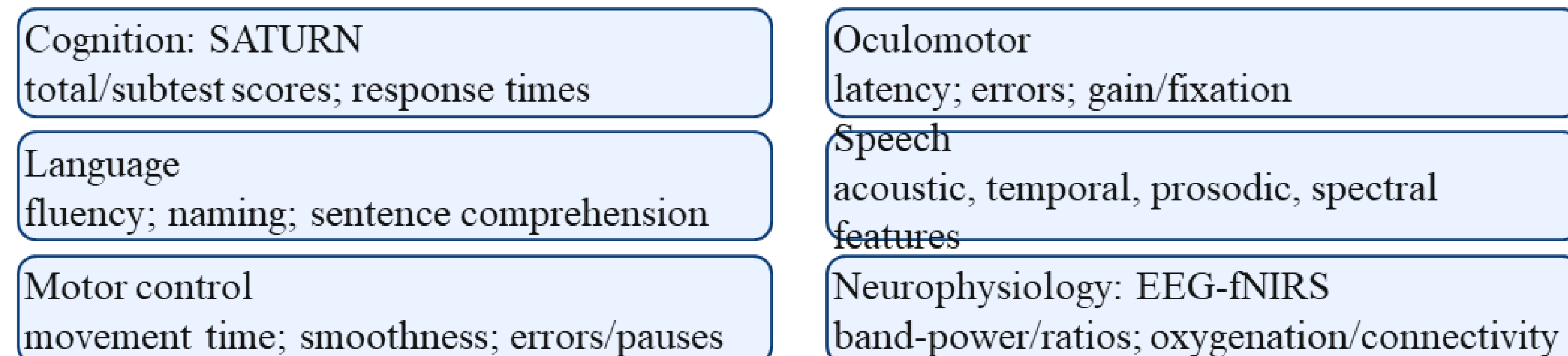
- Prospective, longitudinal diagnostic-validation pilot at CAMH with 60 adults: healthy control (HC), mild cognitive impairment (MCI), and AD (n = 20/group).
- Single-domain and multimodal AI/ML models will be evaluated using participant-level, leakage-aware cross-validation for feasibility, diagnostic accuracy, and longitudinal monitoring.

At each timepoint

One in-person clinical visit and one remote, self-administered digital assessment, ideally within ± 14 days of each other.



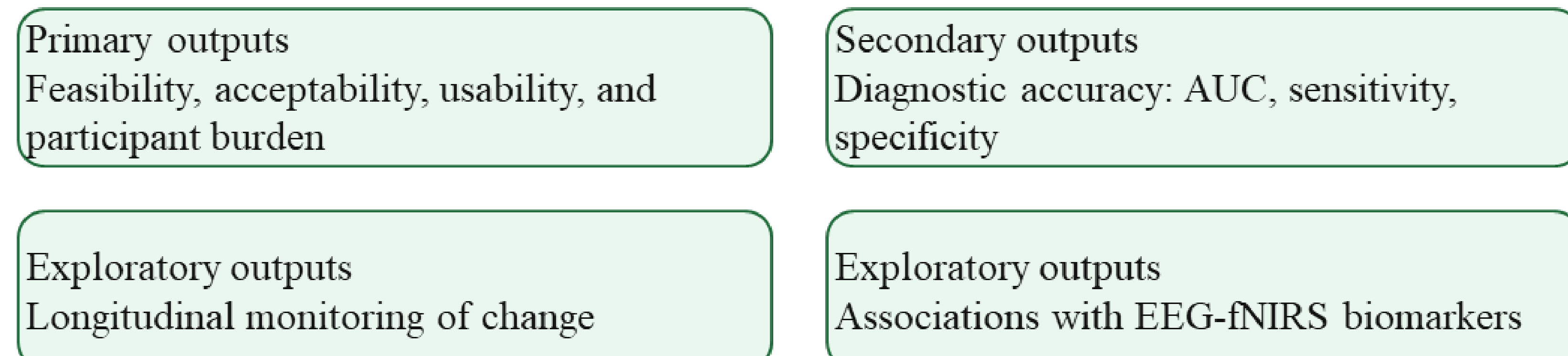
Input domains and candidate feature families



Preprocessing and quality control
Automated device/signal checks → data cleaning and standardization → missing-data handling → feature reduction/selection within cross-validation

Feature extraction and modeling
Single-domain models → multimodal feature fusion → cross-validated machine-learning models
Participant-level 5-fold stratified cross-validation

Study outputs



Implementation measures
SUS, UBS, satisfaction, completion rates, technical issues, and quality-control pass rates

Aims

- ❖ Evaluate feasibility, acceptability, usability, and participant burden of MonitorCog-AI.
- ❖ Assess diagnostic accuracy and whether multimodal AI outperforms the best single-domain model.
- ❖ Explore 12-month longitudinal change and associations with EEG-fNIRS and clinical measures.

Key Hypotheses / Success Criteria

- $\geq 80\%$ complete baseline plus ≥ 1 follow-up
- $\geq 75\%$ rate usability $\geq 4/5$
- Multimodal AUC ≥ 0.80
- Multimodal AI > best single-domain model

Discussion/Impact

- ❖ Integrates cognition, speech/language, oculomotor, motor, and EEG-fNIRS markers within one AI-enabled framework.
- ❖ Designed for remote, repeated assessment, potentially improving access for older adults in rural or underserved settings.
- ❖ Multimodal fusion may capture complementary manifestations of cognitive decline beyond single-domain tools.
- ❖ The longitudinal design supports detection of within-person change over 12 months, not only one-time classification.
- ❖ If feasible and sufficiently accurate, MonitorCog-AI could support earlier, scalable assessment and monitoring, informing future multi-site validation and clinical implementation.

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