#1

Validating an AI-enhanced remote patient monitoring platform for orthostatic vital signs

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MassAITC Aging Focus Pilot Core

MassAITC
Massachusetts AI and Technology Center for Connected Care in Aging & Alzheimer's Disease

Background

Orthostatic Hypotension

- Orthostatic Hypotension (OH) affects nearly **1 in 3 older adults** and **increases the risk for falls by 2.5X**
- Common side effect of BP medications
- **Unmet need**: current home methods fail to detect myriad forms of orthostatic intolerance, leading to poor management of OH

Existing Methods

BP Cuff

+ Inexpensive ($50)
- Doesn't capture real time hemodynamics
- Measures central BP, not cerebral perfusion

Continuous BP (Finapres)

+ Real time hemodynamics
- Too expensive ($50K) for home use
- Measures central BP, not cerebral perfusion

Pilot Objectives

SA1: Validate TRACE in home-like laboratory

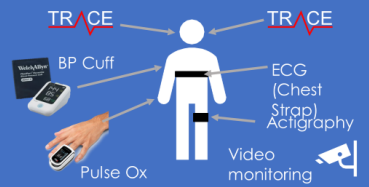
8-hour monitoring study

Active Standup Test (AST)

Intraday Variability

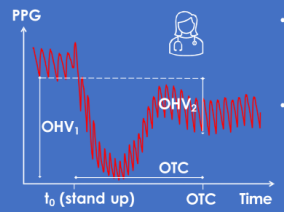
- Evaluate orthostatic vitals with multiple ASTs throughout the day
- Evaluate **intraday changes** in orthostatic vitals due to hydration, meals, bedrest, physical activity

Comparison with other sensors



- Compare TRACE biometrics with validated methods including heart rate, blood pressure, pulse ox, and activity monitors
- Survey comfort and usability

SA2: Physician Guide



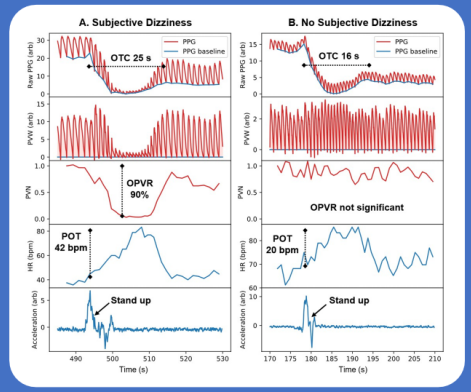
- Physician guide on utilizing TRACE metrics for diagnosis
- Collaboration with autonomic specialist Prof. Dong-In Sinn (Stanford)

SA3: FDA Presubmission

- Early engagement with FDA is recommended as first step for FDA approvals
- Presubmission packet
- Presubmission meeting to obtain feedback from FDA regarding future clinical trial

Future Implications: Fall prevention

- This work is significant because it seeks to prevent fall-related injuries, which impacts nearly 40% of adults over 65 and costs the US healthcare system >$50B annually.
- Preliminary data shows that TRACE can quantitatively measure loss in blood volume during standing, the root cause of lightheadedness upon standing
- Remote monitoring of OH can help physicians better manage and treat OH



TRACE Product Concept

- TRACE is a **patented** wearable that measures orthostatic vitals due to its unique earlobe form factor
- TRACE provides 4 orthostatic vital signs: Orthostatic Hypovolemia (OHV), Postural Orthostatic Teachycardia (POT), Orthostatic Time Constant (OTC), and several others

- Beat to Beat Heart Rate
- Hemodynamics
- **Orthostatic Vital Signs**
- Respiratory
- Temperature
- Posture/ Activity

Time **R**esolved **A**cquisition and AI **C**ontextual **E**valuation

1010
1010

Acknowledgements

TRACE technology has been developed and validated with funding from the following sources.

- MassAITC funding from National Institute on Aging grant P30AG073107
- Michigan Technology Research and Commercialization Fund (MTRAC), from the Michigan Economic Development Corporation (MEDC)
- Michigan Health Endowment Fund (MHEF)
- NIH ACHIEVE GREATER from National Institute of Minority Health Disparities (NIMHD)
- Wayne State University

#2

Let's Talk Tech - the first tool to empower shared decision making about technologies to support dementia care

Clara Berridge PhD, MSW, Natalie Turner, LMSW, School of Social Work, William Lober MD, MS, School of Nursing

PennAITech

SCHOOL OF SOCIAL WORK UNIVERSITY of WASHINGTON

CIRG Clinical Informatics Research Group

Technologies to support dementia care at home have outpaced our understanding of how to help people learn about and think about using them. The digital divide will not be bridged if we leave families to navigate this complex landscape alone. Let's Talk Tech helps care partners (CPs) and people living with dementia (PLWD) understand technologies and balance a desire for monitoring and safety with PLWDs' dignity and wishes. Grounded in the *Theory of Dyadic Illness Management* (Lyons & Lee, 2018), it is designed to help dyads negotiate digital technology use in an informed way.

LET'S TALK TECH is self-administered, completed in ~45 min. by a PLWD and one or more care partner. It facilitates:

1. research-based **education** about data-diverse technologies:
   - location tracking
   - in-home activity sensing
   - in-home web cameras
   - virtual (AI) companions
2. **dyadic communication** about technologies
3. **documentation of the PLWD's preferences**

There are many reasons families require support to make personalized technology use decisions:

- Preferences are diverse and relationally embedded.
- Involvement of PLWD supports ethical use and recognizes personhood.
- Technologies that collect visual, activity, location, or audio data may cause conflict due to their surveilling nature.
- Uninformed decision making is a stressful burden for care partners.

NIH STAGE 1A PILOT ESTABLISHED PRELIMINARY FEASIBILITY & EFFICACY

- n= 29 mild Alzheimer's disease care dyads
- age CPs: 55-83, *M*=68; PLWD: 59-82, *M*=70
- **100% completion** (8/493 total questions skipped)
- Most reported LTT has the right amount of information (>84%), presented in a balanced way (>90%)

Preliminary efficacy:

- Improved CP **preparedness** to make technology use decisions (p =.002)
- +30.5% accuracy in CPs' **knowledge of PLWDs' technology preferences** (p <.001)
- CPs' **technology understanding** of all 4 categories
- PLWDs' technology understanding for 2 of 4 categories
- **CP perception of PLWDs' technology understanding** p <001 for all 4 categories (with involvement implications)
- CPs' **feelings of alignment** (p <001)

PennAITech Work

project start: 9/2023

Barriers to preferred technology use extend beyond education, awareness, and decision-making difficulty. *Could sharing the technology preferences documented in Let's Talk Tech activate the dyads' larger care networks to support them to use technology how they want to?*

Every dyad who completes Let's Talk Tech has a summary document of the PLWD's technology use preferences. Pilot participants reported a desire to share their documented choices with other family and with providers to 1) obtain technology support from their care networks and 2) prevent family conflict.

1. ENABLE PERSON-CONTROLLED SHARING USING STANDARDS: SMARTHEALTH LINKS & FHIR

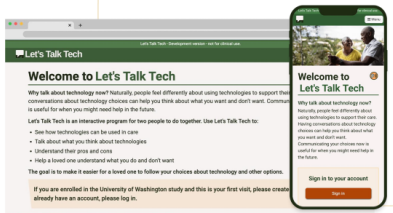
- implement user-controlled, standards-based sharing of preferences using FHIR and the SMART Health Links protocol to share clinical information
- express patient-authored goals & preferences using the FHIR standard
- test new sharing capabilities with dyad users

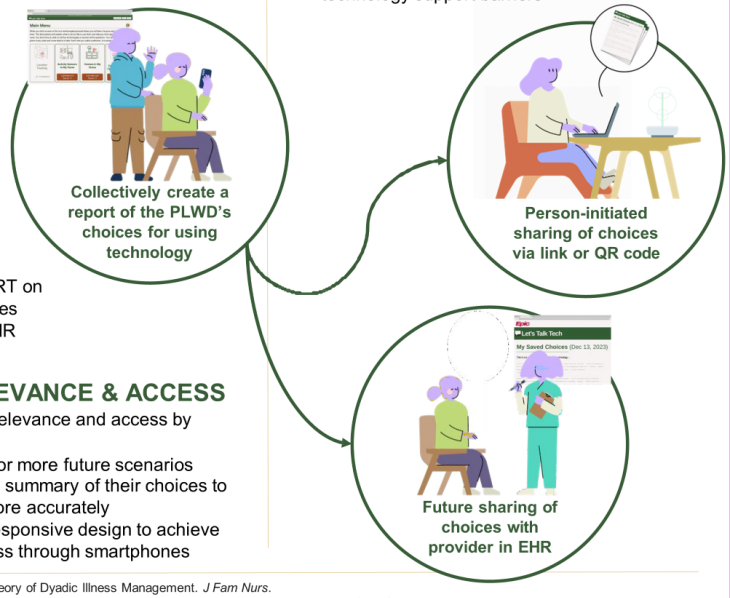
2. EHR INTEGRATION

- implement standards-based EHR integration using SMART on FHIR technology for provider access to patient preferences
- assess AD/ADRD clinician needs and preferences for EHR documentation using test instance

3. BROADEN RELEVANCE & ACCESS

- enhance LTT for wider relevance and access by adding new features:
  - capture preferences for more future scenarios
  - allow users to edit the summary of their choices to reflect their wishes more accurately
  - further optimize the responsive design to achieve wider, equitable access through smartphones





NEXT: Stage 1B mechanistic study

- powered 2-yr pilot study of the Massachusetts General Hospital ROybal CeNter For Behavloral Dyadic ResEarch in Alzheimer's Disease and Related Dementias (CONFIDE-ADRD)
- RCT of LTT mechanisms and individual and dyadic outcomes with racially diverse, English-speaking people living with AD/ADRD or MCI and care partners
- examine sharing behaviors and remaining technology support barriers

Lyons, K.S., Lee, C.S. (2018). The Theory of Dyadic Illness Management. *J Fam Nurs*.
Berridge, C., Turner, N., Liu, L., Fredriksen-Goldsen, K., Lyons, K., Demiris, G., Kaye, J., Lober, W.B. (2023). Preliminary efficacy of Let's Talk Tech: technology use planning for dementia care dyads. *Innovation in Aging*
Berridge, C., Turner, N.R., Liu, L.,Karras, S.W., Chen, A., Fredriksen-Goldsen, K., Demiris, G. (2022). Advance planning for technology use in dementia care: development, design and feasibility of a novel self-administered decision-making tool. *JMIR Aging*
Turner, N., Berridge, C. (2023). How I want technology used in my care and why: Learning from documented choices of people living with dementia using a dyadic advance care planning tool. *Informatics for Health and Social Care*

This Research was supported by the National Institute on Aging of the National Institutes of Health under Award Numbers K01AG062681 and P30AG073105. Pilot study participants were recruited through the University of Washington Alzheimer's Disease Research Center [P30AG066509]. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

#3

Intelligent Cognitive Assistant for Word Retrieval Support for Older Adults with Incipient ADRD

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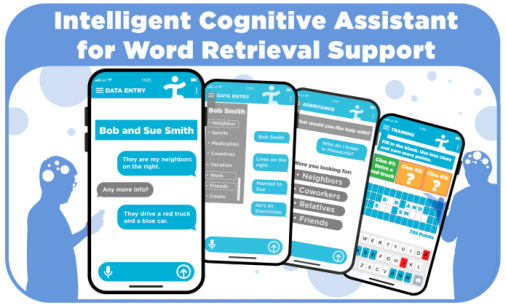
MyWords quickly finds the word a user needs at a particular moment and optionally trains the user to better recall the word in the future.



Aging related word retrieval challenges are intensified by ADRD, affecting nearly 6 million Americans—a figure expected to more than double by 2050. There is a critical demand for innovative, real-time cognitive assistance tools, which recent Natural Language Processing (NLP) advancements are poised to meet.

Key Features

- User-centric
- Adaptive design
- Interdisciplinary approach
- Data-driven insights

Commercial and Translational Impact

- **MyWords App:** Utilizes NLP to create an Intelligent Cognitive Assistant tailored for ADRD word retrieval.
- **Adaptive Learning :** Tailors support by learning from user interactions, easing word retrieval challenges.
- **Broad Application:** Viable for both home and healthcare settings.
- **Scientific Impact:** Offers insights into ADRD through associative semantic network monitoring, aiding research and treatment.

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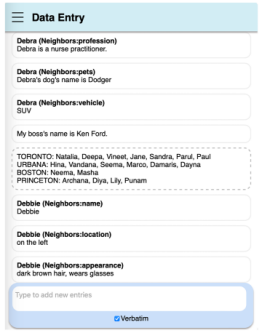
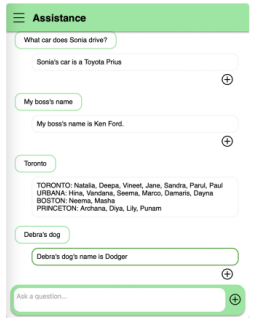
Pilot Project Highlights

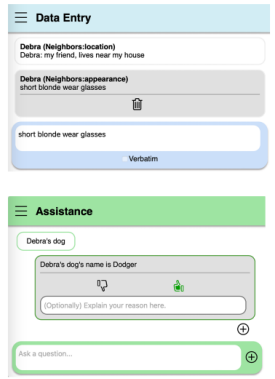
Data Entry Mode



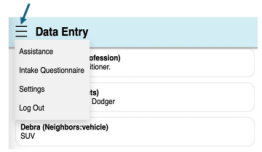
Assistance Mode



Update and Feedback Options



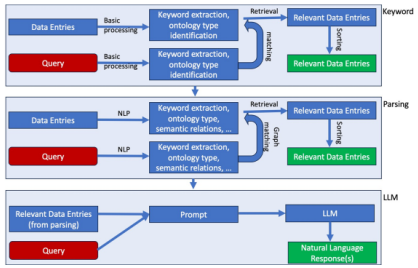
Click Here for the Menu



Participant Information

- **Target Demographics/Criteria:** Older individuals including those with ADRD
- **Recruitment Status:** Initiated usability testing

Processing Pipeline - Extended Mode Setting

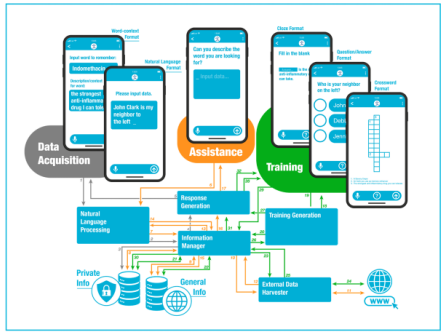


Processing Pipeline - Quick Mode Setting

A 'Query' (above) refers to the message a user inputs when they need the app to assist with recalling a specific word.

Next Steps

- **Complete Usability Testing:** Engage healthy individuals and those with MCI/ADRD
- **Expansion:** Add features based on user feedback to improve the app.
- **Longitudinal Study:** Evaluate app's response appropriateness to users' queries.
- **Funding:** Seek further grants for research and app enhancement
- **Commercialization:** Develop strategy for commercialization.



Takeaways

- **Data Insights:** Tracks memory patterns for personalized support
- **Usability Feedback:** Drives refinements in app design and efficiency, particularly for older users with ADRD
- **Longitudinal Study:** Aims to rigorously assess and tailor long-term efficacy
- **Transformational Potential:** Poised as a communication aid for ADRD
- **Commercialization:** Plans to broaden access and contribute to the discourse on ADRD care

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- National Institute of Neurological Disorders and Stroke. (2024). Focus on Alzheimer's Disease and Related Dementias. Retrieved from https://www.ninds.nih.gov/current-research/focus-disorders/focus-alzheimers-disease-and-related-dementias.
- Alzheimer's Association. (2024). Alzheimer's Disease Facts and Figures. Retrieved from https://www.alz.org/alzheimers-dementia/facts-figures.
- MyWords Webpage: https://github.com/MyWords-app/MyWords.

Acknowledgements
National Institute on Aging grant P30AG073107

#4

Advancing diagnostic excellence for older adults through collective intelligence and imitation learning

Nicholas S. Bishop[1], Christopher Streiffer[1], Matthew J. Press[2,3], Lyle H. Ungar[4], David A. Asch[2,3], MaryAnne Peifer[2,5], Benjamin Schmid[1], Zahra Faraji[1], Gary E. Weissman[1,2,3]

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PennAITech Aging Focus Pilot Core

PennAITech

Background

- Diagnostic error in primary care is a widespread and critical threat to the safety of older adults.
- Despite having been identified as a top research priority by national experts, no differential diagnosis clinical decision support system (CDSS) exists tailored for this population.
- Older adults have unique needs that should guide the development of a diagnostic AI CDSS.

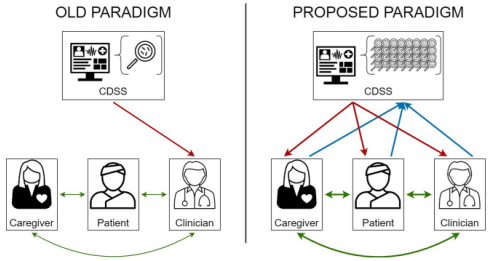

Figure 1: Conceptual model of a CDSS to support the diagnostic process by facilitating communication and history-taking among patients, caregivers, and clinicians. This system provides diagnosis and testing suggestions based on the collective intelligence of peer clinicians.

Objectives

- Train deep learning models to predict the consensus diagnostic and testing behaviors of primary care clinicians.
- Develop and pilot an interactive electronic interface to deliver the predicted information that is acceptable and feasible for patients, caregivers, and clinicians (Figure 1).

Project Achievements

- Trained and validated a preliminary version of the prediction model (*Figure 2, right)*:
  - extracted and processed training and validation data sets based on four years of EHR patient data, including clinical notes, medications, and lab test results;
  - developed an extended list of relevant diagnoses, including a "do not miss list", and manually mapped over 1,600 ICD-10 codes to clinically meaningful diagnostic categories;
  - Trained deep learning models to predict the average clinician treatment and diagnosis for each encounter.
- Developed a front-end, web-based, interactive cloud interface to display the outputs of the prediction models (*Figure 3, below*):
  - Models updated predictions as patients, caregivers, and clinicians enter additional information.
  - Updated outputs displayed to users in real-time.

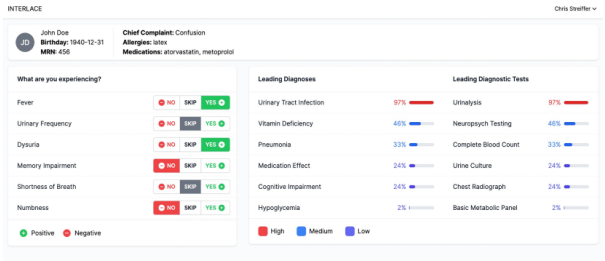

Figure 3: The interactive interface of the prediction models. Patient information is displayed at the top. A list of potential symptoms is on the left side and can be modified in real-time. A list of the predicted diagnoses and their probabilities is in the center. A list of the predicted testing plans and their probabilities is on the right. The predicted outputs change based on the symptoms that are identified as present (YES), absent (NO), or unconsidered (SKIP).

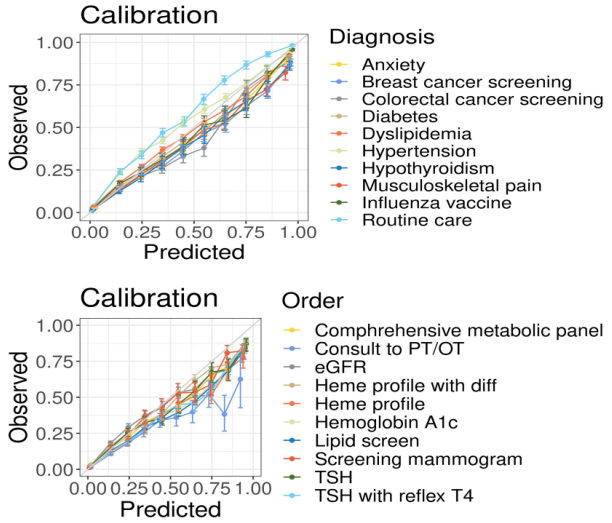

Figure 2: Performance of the prediction models demonstrating excellent calibration for identifying the most common suggested diagnoses (top panel) and tests (bottom panel) in primary care encounters for older adults.

Future Directions

- This tool would be the first fully documented, open-source, diagnostic CDSS appropriate for the broad scope of primary care, in general, and for older adults, in particular.
- Our methodology has applications outside of primary care and would create a roadmap for developing AI CDSS in other contexts with high clinical uncertainty.
- The proposed tool is well suited to several commercial opportunities and is likely to be appealing to health system operational leaders to improve documentation and clinical workflows.

pair Palliative and Advanced Illness Research Center

Penn LDI Leonard Davis Institute of Health Economics

Acknowledgements: This study was supported by funding from the Penn Artificial Intelligence and Technology (PennAITech) Collaboratory for Healthy Aging, National Institute on Aging (P30AG073105).

#5

EyeControl-Med: An AI Communication Platform for Older Patient Engagement and Delirium Management, and Staff Burden Reduction

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[1] John Hopkins University Department of Psychiatry, Baltimore, MD;
[2] EyeFree Assisting Communication Limited, Israel
JH AITC Aging Focus Pilot Core

Clinical Background

- **Delirium:** is a frequent complication in critically ill, older ICU patients, affecting up to 80% of those on ventilators. It leads to higher mortality, longer hospital stays, increased dementia risk, and over $200B in annual U.S. healthcare costs.
- **ICU delirium** has significant long-term effects, extending beyond discharge, including **cognitive decline and an increased risk of dementia**. While effective communication and reorientation interventions have shown promise in managing delirium, implementation challenges persist due to barriers such as limited resources and nursing bandwidth.

Project Background

- **EyeControl-Med (EC-M):** is an innovative AI-powered wearable communication solution designed to not only manage delirium in the ICU but also address its long-term effects post-discharge. By facilitating communication and reorientation interventions, EC-M aims to improve patient outcomes and reduce the risk of cognitive decline and dementia in the geriatric ICU population
- **Features:** audio streaming, family messages, remote monitoring, & reorientation.
- **Prior work**: promising results in adult ICU populations on EC-M's efficacy for delirium reduction.
- **Objective:** Evaluate the feasibility and efficacy of EC-M intervention in geriatric ICU patients focusing on addressing **long-term outcomes such as post-ICU syndrome**.

Pilot Project Highlights

Figure 1: EyeControl-Med Headset

Duration	52 weeks
Location	ICU
Cohort	30 patients

Table 1: Study Overview

Study Aims

1. Assess how EC-M impacts duration and fluctuation of delirium-free days in patients using EC-M compared to conventional treatment
2. Evaluate delirium detection accuracy of EC-M's automated **Confusion Assessment Method for the Intensive Care Unit (CAM-ICU)** compared to manual assessments.
3. Track longitudinal effect of delirium on cognition and dementia at admission and 6 months post-discharge, comparing EC-M to control group, **utilizing the IQCODE** and the **QDRS** assessments.

Secondary Aims

1. Refine work-flow integration for EC-M implementation
2. Collect feedback and observational data from healthcare staff and families.

Study Design

- 52-week randomized controlled trial at Johns Hopkins, enrolling 30 ventilated ICU patients over 55 years old
- **Methods:** CAM-ICU, Informant Questionnaire on Cognitive Decline in the Elderly (IQCODE), Quick Dementia Rating System (QDRS), MoCA assessment; alongside **AI-powered** EyeControl-Med for communication, reorientation, music, family engagement
- **Results:** Our hypothesis suggests reduced delirium duration/fluctuation, improved detection accuracy, lower cognitive decline
- **Next steps:** Potential commercialization and wider implementation plans

Implications

- **EyeControl-Med** offers an innovative **AI-based** approach to improve ICU patient communication, delirium management, and clinical workflows
- **Potential impacts** include reduced delirium, shorter hospital stays, lower costs, improved patient/family experience, and reduced dementia risk
- This study highlights the importance of **effective communication interventions** and potential for EyeControl-Med to establish a new standard of care

Figure 2: EyeControl-Med device

Funded by the JHU AITC GY2 grant 138809.

#6

Real-Time Remote Monitoring of Confirmed Medication Adherence

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Elizabeth Goldberg, MD, ScM
etectRx, University of Colorado Denver
PennAITech Aging Focus Pilot Core

University of Colorado Denver | Anschutz Medical Campus

Abstract

The FDA-Cleared ID-Cap™ System is a seamless, end-to-end solution for remotely monitoring, tracking and improving medication adherence in real time. Using the world's first and only off-body ingestion event monitor, along with Alexa integration, enables real-time medication adherence monitoring and encouragement to assist with aging in place.

Milestones

- ✓ Design gathering and acceptability study completed
- ✓ Several software solutions with design informed by the completed study are in the verification phase
- ✓ Reader design completed with UCD also enables real-time incontinence monitoring at home and in assisted living facilities

Pilot Project Highlights

Key Participant Metrics

Participants Enrolled	Patients Enrolled	Care Provider Enrolled	Male Participants	Female Participants	Mean Participant Age
15	14	1	7	8	76.6

Identified Themes

- **93%** Have smartphones, predominantly iOS
- **80%** Can download apps by themselves from app stores
- **2-15** Meds per day. **93%** take all meds at one time
- **87%** Take meds each day at the same time
- **93%** Have heard of Alexa and **20%** are actively using Alexa
- **33%** Actively use some type of voice assistant
- **73%** Use pill boxes to help with medication management and believe it helps, but are concerned about effectiveness in the future
- **93%** State they are independently managing their meds
- **87%** Have Wi-Fi at home

Key Design Takeaways

- **93%** Think reminders would be helpful
- **33%** Would also like reminders on their phone
- **60%** Think secondary reminders would also be helpful
- **60%** Would allow caregiver to help with setup
- **33%** Stated they would setup device
- **67%** Believe a visual display of ingestion history would be helpful
- **53%** Would like device to identify you before making reminder announcement

Conclusions

Of subjects expressed concern about devices "listening" and security of devices like the Echo – Maybe consider speaker instead?

Believed that they would need help eventually with medication management beyond that which is provided by a pill box

- The vast majority believed a home reminder system would be helpful but would need help making adjustments to the device
- Strong consensus that caregiver should receive notification regarding medication non-compliance
- Verbiage consensus from reminder <Name>, <Medication>, time to take or some variant. **(John, please take your XXX at 8am)**

Acknowledgements

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National Institute on Aging Grant 1R43AG073011-01A1

#7

Improving Mobility for Dementia Alleviation in Older Adults via AI-Powered Affordable Exosuits

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Junxin Li, Chien-Ming Huang, Hao Su
Johns Hopkins University, Picasso Intelligence, North Carolina State University
JH AITC AD/ADRD Focus Pilot Core

Empower Human via Innovation

Motivation

- Increased physical activity can lower blood glucose levels and the likelihood of dementia
- Current solutions are tethered (only accessible in clinics) and restrict movement

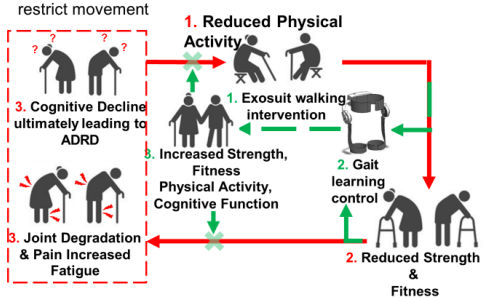


Figure 1: Our AI-powered hip exosuit has the potential to break the inimical cycle of declining health by facilitating improved mobility.

Objectives

- Learning-based personalized control for walking assistance via lightweight exosuits
- Evaluate mobility biomechanics benefits of exosuit-assisted walking in the field
- Revenue model and cost analysis for product translation from clinical to home use

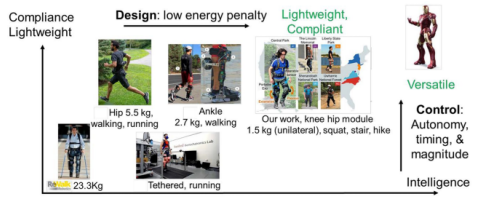


Figure 2: Comparison of new exosuit to existing paradigms.

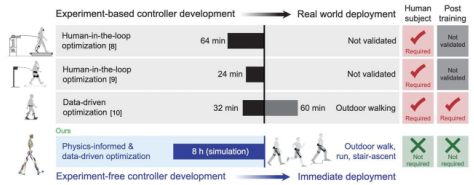


Figure 3: Experiment-free learning algorithm for exosuit control.

Pilot Project Highlights

	Geared Motor with Force/Torque Sensor	Series Elastic Actuator	Quasi Direct Drive Actuator [Ours][7]
Compliance	Low ✗	Medium ~	High ✓
Bandwidth	High ✓	Low ✗	High ✓
Efficiency	Low ✗	Medium ~	High ✓
Actuation Paradigm	High ratio gear; Conventional motor; Load	Conventional motor; Spring; Load	High torque density motor; Load; Low ratio gear

Figure 4: New actuator paradigm for exosuits that facilitates high compliance, bandwidth, and efficiency.

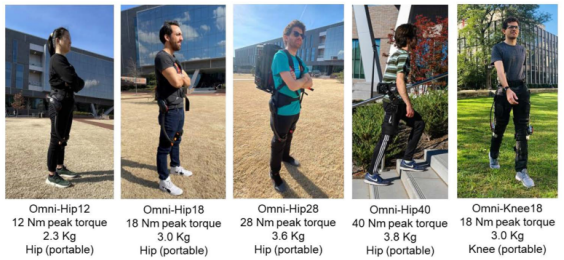
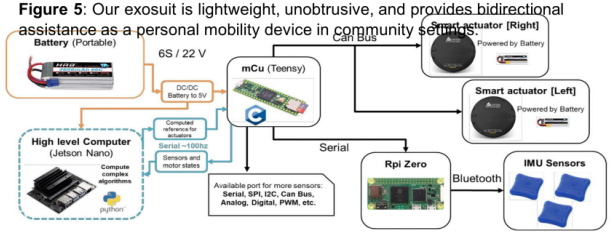


Figure 5: Our exosuit is lightweight, unobtrusive, and provides bidirectional assistance as a personal mobility device in community settings.



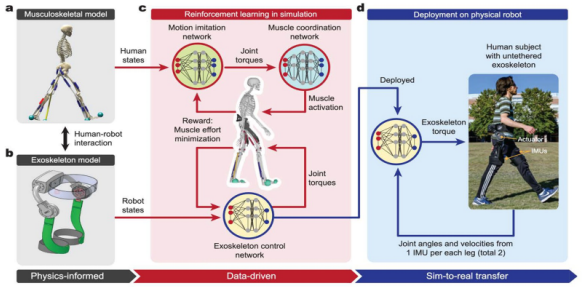


Figure 7: Deep neural network reinforcement learning based controller uses offline musculoskeletal agent simulation via imitation learning to produce assistive torque for multiple activities.

Conclusions

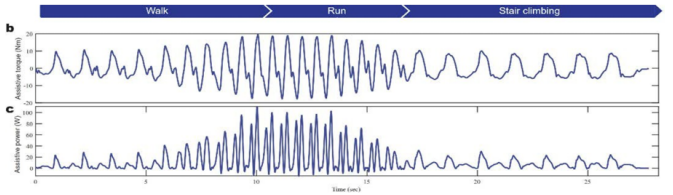


Figure 8: Controller provides autonomous assistive control across three locomotion activities.

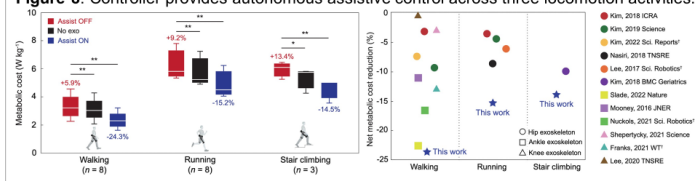


Figure 9: Significant reduction of metabolic cost. **Figure 10**: Highest metabolic cost reduction.

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Acknowledgements

National Institute on Aging grant P30AG073104

#8

Device-Free Wi-Fi Sensing Technology to Assess Daily Activities and Mobility in Low-Income Older Adults

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PennAITech AD/ADRD Focus Pilot Core

PennAITech

BACKGROUND

- **Low-income, minority older adults** are at an increased **risk of cognitive impairment** and dementia.
- Cognitive impairment affects *the ability to perform and manage daily activities and mobility behaviors*.
- **Assessing the ability to perform daily activities and detecting the changes in these abilities early is crucial,** but often **difficult** in this population due to **limited resources**.
- Traditional activity and mobility assessment tools are primarily self-report, subjective, and episodic.
- Existing smart home sensors show **limited ability to detect different types of human behaviors** (e.g., eating, preparing meals).
- Sensing devices are not readily available to older adults with health disparities due to cost and information barriers.
- There is a need to develop **new sensing technology that can characterize and quantify daily activities** while also *being discreet, affordable, and requiring minimal user engagement*.

PROJECT GOAL

To develop a Channel State Information (CSI)-based device-free Wi-Fi sensing system using ML classification to localize and recognize different in-home daily activities and mobility. Our ultimate goal is to create an affordable cutting-edge system that uses Wi-Fi signals for assessing physical function in low-income older adults.

Our Wi-Fi Sensor

PILOT PROJECT HIGHLIGHTS

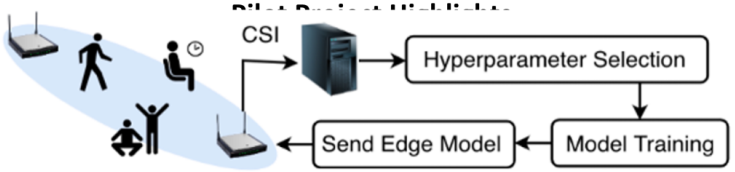
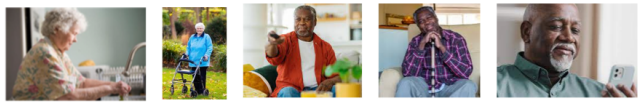


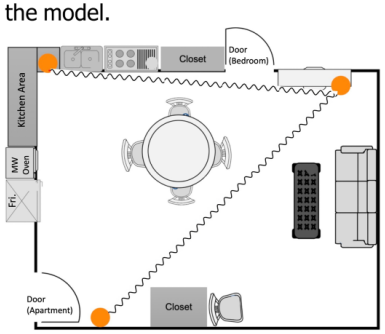
Figure 1. Overview of the typical WiFi sensing system

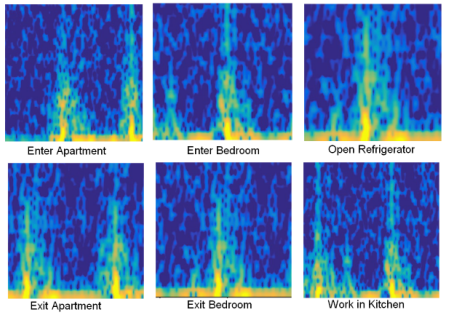
Technology Description: We leverage existing Wi-Fi infrastructure or use low-cost devices to transmit Wi-Fi signals in the home environment. The CSI of Wi-Fi signals in all subcarriers are used for communication between Transmitter and Receiver devices. We employ ML algorithms to process the CSI data and extract different activity features, such as sitting, meal preparation, kitchen sink use, watching TV, phone use, and entering/exiting home.



Participants: Individuals living in low-income senior housing (aged 60 and older) with and without mild cognitive impairment.

Preliminary Results: Seven participants have enrolled in the study. The following images show a participant's floor map with our setup and the spectrogram images obtained from 6 different activities of the participant. We are developing a Convolutional Neural Networks (CNN) model to establish the accuracy of activity detection based on the preprocessed raw data. Our CNN model based on a single participant was 68.8% accuracy. We will use data with more variations to fine tune the model.





CONCLUSIONS & IMPLICATIONS

- **The ability to identify and differentiate human activities** will be improved when algorithms to disambiguate the data are fully available.
- This initiative aims to empower low-income older adults by harnessing the power of Wi-Fi sensing technology and ML to detect functional decline early that signals cognitive impairment. **By providing an accessible and cost-effective solution, we can improve the lives of older adults with health disparities and enhance their brain health.**
- Wi-Fi sensing system facilitates passive monitoring, which does **not require user involvement**. Our target population has **limited digital technology experience and low IT literacy**. This technology may provide a more effective sensing solution to older adults with cognitive decline, functional impairment (e.g., visual or hearing impairment), limited technology experience, low literacy, and/or lack of technology support, potentially **achieving digital health equity.**

ACKNOLWEDGEMENT

Research reported in this presentation has been supported by the National Institute on Aging of the National Institutes of Health under Award Number P30AG073105 and the Intramural Research Grant from Virginia Commonwealth University School of Nursing.

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#9

IN-home Cognitive Improvement Training using EEG-NFB

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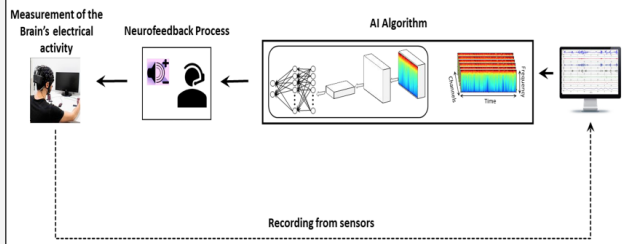
Introduction:

- Alzheimer's disease places an enormous psychological and emotional burden on patients and caregivers; it also places tremendous financial strain on families and healthcare systems.
- In 2023, Alzheimer's and other dementias cost the nation $345 billion — not including the value of unpaid caregiving.
- EEG neurofeedback is applied to mitigate cognitive impairments and behavioral alterations in dementia and various neurological conditions. This method trains individuals to modify their brain waves through operant conditioning.
- Deep learning techniques are increasingly utilized in analyzing EEG data to identify and capture instances of peak working memory performance. By leveraging complex neural networks, these methods can discern intricate patterns in brain activity that correspond with optimal cognitive function.

Aims:

Purpose: developing a unique method for ameliorating the progression of cognitive impairment in persons with Alzheimer's Disease and other dementias.

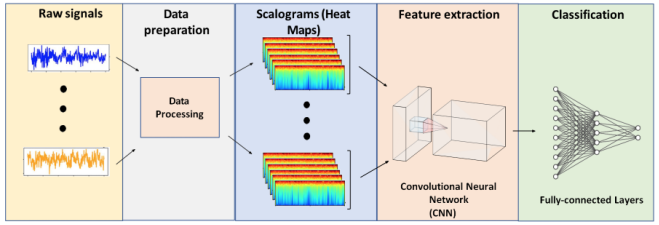


Aim 1. Design a machine learning algorithm to capture EEG patterns associated with peak working memory performance in near real-time. Fine-tune the machine learning model based on individual patient EEG characteristics and feedback thresholds.

Aim 2. Develop hardware/software integrating EEG recording, evaluation of EEG components defined in Aim 1, and modulate music volume contingent on the presence of EEG components associated with peak working memory performance.

Methods:

- A CNN pipeline algorithm trained on a publicly accessible database consisting of EEG data recorded from 36 subjects performing mental arithmetic tasks.



Data preprocessing:

Denoising:

- Independent Component Analysis (ICA) to eliminate the artifacts (eyes, muscle, and cardiac overlapping of the cardiac pulsation).
- Band pass filter with the cut-off frequency 0.5-45 Hz to remove baseline noise
- Notch filters (50-60 Hz) to remove line noise

Specific 10-20 system sites:

- F3, F4, Fz, P3, P4, Pz; focused on frontoparietal axis dynamics.

Data segmentation:

- Segments of 2 seconds with 50% overlap.

Scalogram:

Compute the scalograms (heat maps) of each EEG signal segment using the Continuous Wavelet Transform (CWT) with a 'Morlet' wavelet at a scale of 128.

CNN Architecture:

Three convolutional layers followed by 2x2 max-pooling layers.

Classification:

Three fully connected layers with a dropout probability of 25%.

Accomplishments:

- Developed an AI model for classifying cognitive tasks using publicly available data.
- Designed a hardware/software infrastructure for collecting data, utilizing wearable dry EEG electrodes and BCI technology.
- Established individualization assessment protocol for personalization of the AI model.

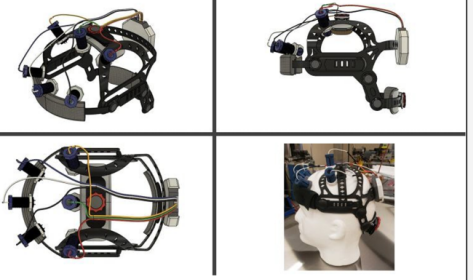
Results:

- The initial model (Aim 1) achieves a 79% f1-score overall and is 84% sensitive to detecting working memory peaks.

	Train	Test
Accuracy	85.03 %	67.59 %
Precision	0.87	0.75
Recall	0.94	0.84
F1_Score	0.90	0.79

Establishment of Individualization Assessment:

- Recording EEG during the performance of a task modeled on the WAIS-IV Letter-Number Sequencing task.
- String length increases until failure of 2 sequential strings of the same length, then length reduces by 1. Then, it continues to increase until failure repeats. The process repeats until the threshold is reached (~20-minute duration).
- This procedure is then used to identify features of the EEG activity associated with peak performance vs. working memory failure.



Next steps:

- Refine our deep learning model using experimental data. This involves updating the model's parameters with the new information and applying a fine-tuning technique.

Acknowledgments: This work is supported by the National Institute on Aging grant P30AG073107, and HSSA RFP #6: Innovative Health Care Delivery & Translative Research Matching Grant.

#10

University of Massachusetts Amherst

Validating Novel Sleep Sensors and Devices in Older Adults

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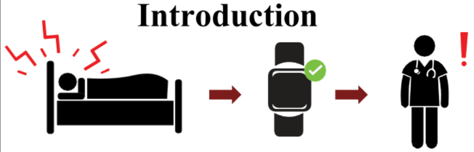
Introduction



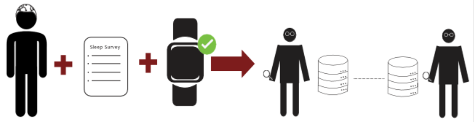
• Good sleep is criticial to health, and poor sleep often preceeds the onset of Mild Cognitive Impairment (MCI).[1-2]

• Early detection of poor sleep may provide an opportunity to identify MCI earlier, and may provide avenues to reduce the onset and severity of MCI. [3]

• Many commerical devices can track sleep non-invasively at home, which could be monitored long-term by caregivers or clinicians offsite. [4]

• **While several studies have examined the accuracy of commercial sleep monitoring devices in young adults, more studies are needed to examine the accuracy of these devices in older adults with and without MCI.** [5]

Study Objectives

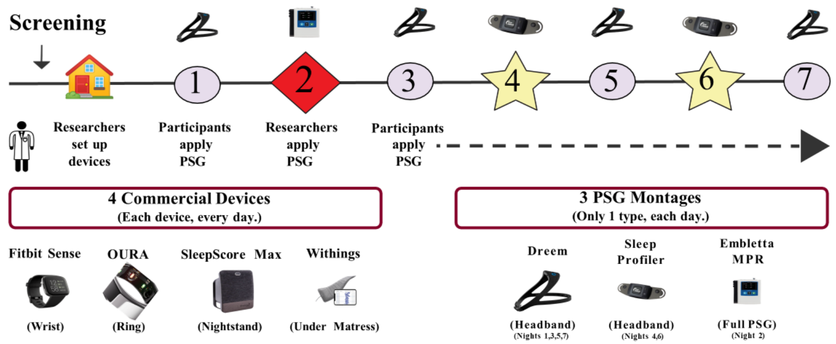


• To evaluate the sleep monitoring performance, compliance, and usability of commercial devices compared to polysomnography (PSG) and self-reported sleep in 30 older adults, 30 older adults with MCI, and 30 young adults.

• To develop a public database of physiological signals, sleep measures, and questionnaires to faciliate research evaluating the accuracy of commerical sleep monitoring devices, and potentially the identification of novel biomarkers for the early detection of MCI.

• Here, we preliminarily compared total sleep time reported by the Dreem headband and Sleep Profiler, to self-reported total sleep time in older adults and young adults.

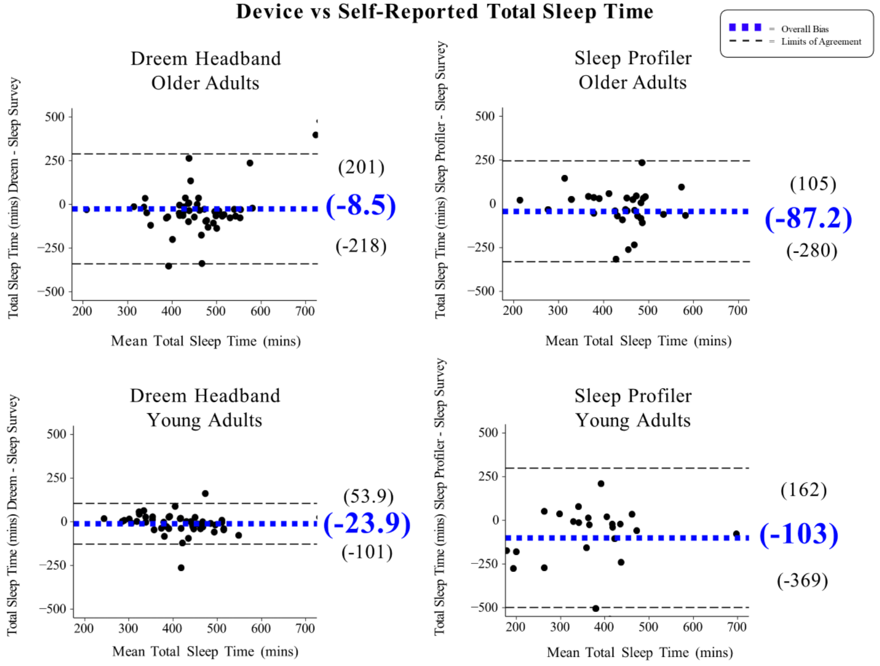
Full Study Protocol



• For 7 days, participants wore 4 commerical sleep monitoring devices, completed a daily sleep survey, and used one type of PSG at home. On Day 1, researchers set up the devices and taught participants to use them. In the evening, participants self applied the Dreem headband. In the evening on Day 2, researchers applied the Embletta MPR, a full PSG montage. On Days 3-7 participants used all 4 devices, completed a sleep diary, and alternated between self-applying the Dreem headband or Sleep Profiler.

Preliminary Results for Dreem and Sleep Profiler

Device vs Self-Reported Total Sleep Time



Participant Sample Characteristics and Cognitive Assessment Scores

	n	Age (years)	Gender (F:M)	Height (cm)	Weight (kg)	TICS	Mini-MoCA	Full-MoCA	MMSE	AD8
Younger Adult	17	20.8 (1.2)	15:2	164.4 (3.3)	68.3 (14)	36.1 (2.6)	26.8 (1.6)	28.5 (1.9)	28.4 (1.1)	0.1 (0.5)
Older Adult	21	65.7 (5.8)	15:6	169 (7.7)	70.8 (12)	36.7 (2.1)	25.9 (3)	28.4 (2.9)	26.4 (1.4)	0.4 (1.2)

• Participants were healthy and scored within normal ranges on cognitive tests.

Conclusions

• In both older adults and young adults, the Dreem headband tended to report total sleep times that were similar to self-report. The Sleep Profiler tended to underestimate total sleep time in both groups.

• For the Dreem headband, the limits of agreement were wider in older adults than in young adults. Limits of agreement were wide in both older adult and young adult groups for the Sleep Profiler.

• Overall, total sleep time reported by the Dreem headband was more consistent with self report than total sleep time reported by the Sleep Profiler.

Future Directions

• Our objective is to compare sleep measures reported by all 4 of the commercial devices to corresponding measures collected by self-report, the Dreem headband, the Sleep Profiler, and the Embletta MPR.

• We will continue to diversify our sample, and recruit participants who indicate Mild Cognitive Impairment based on their scores from the Telephone Interview for Cognitive Status.

• We will develop a public database of the physiological signals, sleep measures, and all data collected by each of the 4 devices, 3 types of PSG, and all of the questionnaires. Data will be provided at the highest resolution possible.

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AT THE UNIVERSITY OF MASSACHUSETTS AMHERST

#11

A novel insole solution used in daily life to identify and mitigate falls and frailty.

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[1]Tufts University, [2]Walk With Path, [3]Arizona State University
JH AITC [AD/ADRD *or* Aging] Focus Pilot Core

Background

- Falls are leading cause of injury and hospitalization in people >65
- Balance difficulties in walking is a risk factor for falls
- Remote, in-home monitoring of gait and balance may improve ability to track and treat fall-prone people.
- An instrumented insole was developed to provide real-time balance and gait metrics to patients and / or clinicians.
- This tool could assist in mitigating falls and relieve economic burden.
- However, validity of insole mobility outcomes and potential usability in the clinic must be assessed.

Objectives

- Validate insole walking and standing balance to gold-standard
- Validate if walking and balance patterns are relevant to prospective fall history
- Validate usability of insoles by end-users

Methods and Results

Figure 1: Path Feel instrumented insole

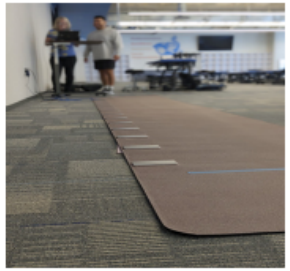


Figure 2: GaitRite mat

Methods

- 31 participants (≥ 50 y.o.) completed a single data collection
- 11 walking & balance assessments were completed, including:
  - Walking at normal pace with & without a distracting task
- Data collected via GaitRite mat (gold standard) and insoles
- Insole and mat synchronization was completed via visual first contact time. Algorithms for pressure and acceleration and additional methods such as python, numpy and pandas

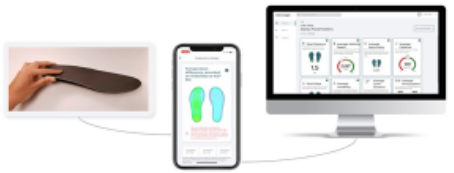
Results

Table 1: Step to step comparison insole to GaitRite mat ("sample size" = number of steps included in analysis)

Gait Parameter	Sample Size	Mean Absolute Error (1 standard deviation)	Accuracy (100% - MAE)
Stride velocity	644	6.76 ± 4.73%	93.24 ± 4.73%
Stride duration	639	2.34 ± 1.21%	97.66 ± 1.21%
Stride length	641	8.33 ± 4.46%	91.67 ± 4.46%
Step length	642	8.39 ± 5.47%	91.61 ± 5.47%

Conclusions

- **Insoles provide accurate gait parameters compared to gold standard** (collection ongoing)
- Next steps
  - Relate outcomes to fall history
  - Conduct focus groups
- Collaboration with Carey Business School for marketing
- Target stakeholders:
  - Individuals at risk for falls
  - Healthcare professionals including physicians, nurses, social workers, physical therapists and occupational therapists



Acknowledgements

JH AITC funding via National Institute on Aging grant P30AGo73104.

#12

Passive measures of physical activity as an early biomarker for cognitive impairment

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Massachusetts AI and Technology Center for Connected Care in Aging & Alzheimer's Disease

Introduction

- A growing body of research indicates that regular physical activity can mitigate the risk of cognitive decline among older adults.
- The advent of digital technology facilitates the collection of passive measures of physical activity.
- The objective of this study is to examine the association between physical activity measures and the neuropsychological (NP) tests across multiple cognitive domains and evaluate the added predictive power of physical activity measures for the prediction of dementia.

Methods

➢ **Study population**

- This study included participants from the Framingham Heart Study, a community-based cohort with longitudinal surveillance for incident dementia.

➢ **Physical activity assessment**

- All participants were instructed to wear an omnidirectional accelerometer (Actical model no. 198-0200-00; Philips Respironics Inc.,Murrysville, PA) around their hip during waking hours, excluding any times spent bathing.
- Activity levels per minute were defined by intensity thresholds: ≥1535 counts for moderate to vigorous physical activity (MVPA) and ≤100 counts for sedentary time.
- Sedentary time was normalized to wear time, calculating it as a proportion of an 18-hour day.
- The average daily steps were computed across all valid days, with a cap at 20,000 steps to address outliers.
- 42 physical activity measures were included in this study.

➢ **NP assessment**

- 18 NP tests measuring multiple cognitive functions including verbal and visual memory, verbal fluency, attention and concentration, executive functioning, abstract reasoning, visuoperceptual organization, and language.

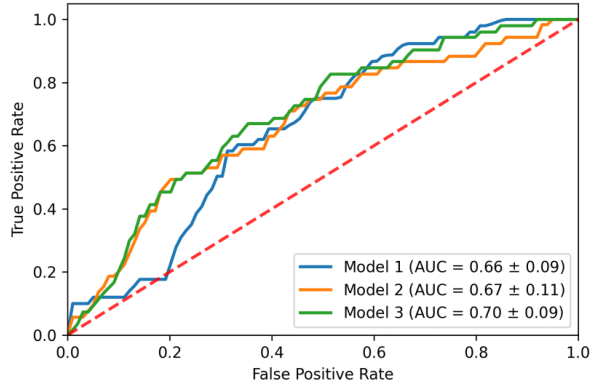
➢ **Ascertainment of dementia**

- Dementia diagnosis at FHS was made by a review committee, including at least one neurologist and neuropsychologist. Diagnosis criteria followed the DSM-IV standards.
- Incident dementia cases were participants initially cognitively intact but diagnosed with dementia during follow-up.

- **Statistical analyses**
- Linear regression models evaluated the association between physical activity measures and NP tests, adjusting for age, sex and time interval between NP and physical activity examine dates.
- Cox proportional hazards model assessed the association between incident dementia and physical activity measures, also adjusting for age and sex.
- Investigated the predictive improvement of physical activity measures for incident dementia using ROC analysis and the CatBoost model.
- Model 1 used predictors such as age, sex, and education.
- Model 2 included these predictors plus 42 physical activity indicators.
- Model 3 added age, sex, education, and specific physical activity measures with significant association to NP tests.

Results

- Our study included 1569 participants from the FHS Offspring cohort (mean age: 70± 8 years; 54.0% women). There are 53 participants with incident dementia with mean follow up time of 9 years.
- min/day (average) of medium movement (80-99 steps/1 min) on adherent days was associated with incident dementia with nominal significance (HR: 0.41, 95%CI: 0.20-0.86, *P*=0.018).
- 24 physical activity measures were associated with at least one NP test after Bonferroni correction for multiple testing. min/day (average) of sedentary activity (<= 100 counts/minute) on adherent days was significantly associated with 6 NP tests.
- The physical activity measures can increase the AUC of the baseline model for dementia prediction from 0.66 to 0.70.



Physical activity measure	Description	The most significant NP test	Beta	SE	*P* value	*n*
SOL_SED_DAY	min/day (average) of sedentary activity (<= 100 counts/minute) on adherent days	LMd	0.42	0.10	2.07E-05	6
SOL_LIGHT_DAY	min/day (average) of light activity (101-1534 counts/minute) on adherent days	TrailsA	-0.05	0.01	7.80E-07	2
KIN_SED_DAY	min/day (average) of kin sedentary activity (<=200 counts/minute) on adherent days	LMd	0.37	0.10	0.000160972	4
KIN_LIGHT_DAY	min/day (average) of kin light activity (201-1485 counts/minute) on adherent days	TrailsA	-0.05	0.01	7.48E-08	2
KIN_MOD_DAY	min/day (average) of kin moderate activity (1486-5557 counts/minute) on adherent days	SIM	0.32	0.10	0.00091531	1
CADENCE_0_DAY	min/day (average) of no movement (0 steps/1 min) on adherent days	LMd	0.40	0.10	3.53E-05	5
TOT_BOUTMETA_SEDENTARY_DAY	Total minutes per day accumulated in sedentary intensity activity that lasted for 10 minutes or longer	LMd	0.41	0.10	4.21E-05	4
TOT_BOUTMETA_LIGHT_DAY	Total minutes per day accumulated in light intensity activity that lasted for 10 minutes or longer	TrailsA	-0.04	0.01	6.88E-05	2
STEPS_CENSORED_DAY	Average censored (if CPM <500 then steps assigned 0 value) steps/day monitor was worn on adherent days	TrailsB	-0.15	0.04	2.92E-05	3
STEPS_DAY	Average steps/day monitor was worn on adherent days	TrailsB	-0.17	0.04	3.82E-06	2
STEPS_MIN_DAY	steps/min (average) per day monitor was worn on adherent days	TrailsB	-0.16	0.04	4.97E-06	2
STEPS_MIN_CENSORED_DAY	censored (if CPM <500 then steps assigned 0 value) steps/min (average) per day monitor was worn on adherent days	TrailsB	-0.15	0.04	2.40E-05	2
PEAKDAY1_DAY	average cadence representing the highest 1 minute accumulated (not necessarily consecutive)	TrailsB	-0.22	0.04	1.64E-09	5
PEAKDAY5_DAY	average cadence representing the highest 5 minute accumulated (not necessarily consecutive)	TrailsB	-0.23	0.04	5.94E-10	5
PEAKDAY10_DAY	average cadence representing the highest 10 minute accumulated (not necessarily consecutive)	TrailsB	-0.23	0.04	3.12E-10	5
PEAKDAY30_DAY	average cadence representing the highest 30 minute accumulated (not necessarily consecutive)	TrailsB	-0.22	0.04	7.52E-10	5
PEAKDAY60_DAY	average cadence representing the highest 60 minute accumulated (not necessarily consecutive)	TrailsB	-0.22	0.04	1.83E-09	5
CADENCE_1_39_DAY	min/day (average) of [1-39] steps/1 min on adherent days	TrailsA	-0.04	0.01	4.71E-05	2
CADENCE_40_99_DAY	min/day (average) of [40-99] steps/1 min on adherent days	TrailsA	-0.04	0.01	4.72E-05	2
CADENCE_40_HIGHER_DAY	min/day (average) of brisk movement (>=40 steps/1 min) on adherent days	TrailsB	-0.15	0.04	2.57E-05	2
CADENCE_0_20_DAY	min/day (average) of incidental movement (<=19 steps/1 min) on adherent days	TrailsA	-0.03	0.01	0.000880777	1
CADENCE_20_40_DAY	min/day (average) of sporadic movement (20-39 steps/1 min) on adherent days	TrailsA	-0.04	0.01	4.94E-06	2
CADENCE_40_60_DAY	min/day (average) of purposeful movement (40-59 steps/1 min) on adherent days	TrailsA	-0.04	0.01	7.48E-06	2
CADENCE_60_80_DAY	min/day (average) of slow movement (60-79 steps/1 min) on adherent days	TrailsA	-0.03	0.01	0.000836789	1

Conclusion

- We identified multiple associations between NP tests and physical activity measures suggesting the potential of using passive measures of physical activity as an early biomarker for cognitive impairment.
- Additional research, especially with external cohorts, is needed to validate these findings further.

Acknowledgement

Our study was supported by National Institute on Aging grant P30AG073107

#13

Creation of a Technology-Ready Cohort of Patients with Alzheimer's Disease and Related Dementias and Their Caregivers

Mark C. Eldaief, MD[1], Baeta-Gabriela Simpson[1] and Sudeshna Das, PhD[1]

[1]Massachusetts Alzheimer's Disease Research Center, Massachusetts General Hospital and Harvard Medical School, Boston, MA

Background/Introduction

- Patients with Alzheimer's disease and related dementias (ADRD) are evaluated at infrequent clinical or research visits in artificial settings.
- *This hinders the ability to granularly and accurately characterize disease progression in ADRD.*
- Digital technologies such as digital phenotyping, AI, and machine learning can track cognition, behavior, activity, socialization, and sleep quality in ADRD.
- Such assessments have the advantage of repeated (or continuous) data sampling unobtrusively in real-life, ecologically valid contexts.

Objectives

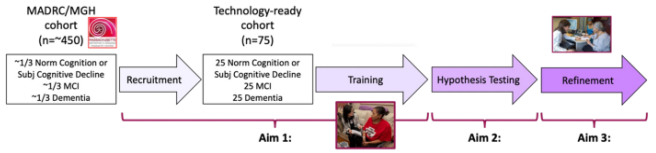
Aim 1: To create a cohort of technology-ready older adults, ADRD patients, and their caregivers.

Aim 2: To use digital assessments to predict cognitive and behavioral declines in ADRD patients.

Aim 3: To assess the ability of these measures to engage ADRD/caregivers and to troubleshoot issues.

Methods

- 75 participants: 25 cognitively normal or subjective cognitive decline, 25 with Mild Cognitive Impairment (MCI) and 25 with mild dementia, aged 55-90 years, and their co-participants will be recruited from our MADRC Longitudinal Cohort. Active and passive data assessments will be collected over 1 year (**Fig. 1**).



- Participants will be instructed on how to use devices/programs through telephone/video support calls and technical issues will be troubleshooted iteratively.
- Passive assessments will be collected through the **Apple Watch™ (series 9)**. This will be worn *continuously (as tolerated) and* will record heart rate, ECG, skin temp, motor activity & sleep.

- Active assessments will be done monthly and will include:

a. Voice recordings on participants' personal smartphones using the **Sonde One** app.
a. Online subjective cognitive concern questionnaires (SCD-Q).
b. Online caregiver distress questionnaires (study partners).
c. Online study adherence questionnaires (study partners).
d. Online mood questionnaires (PHQ-9, NPI, QIDS, HAM-D).

- Subjects will undergo extended cognitive testing through the NIH toolbox at baseline and at 6 and 12 months.
- Subjects can play games (e.g., Solitaire, Tetris) on their personal smartphone by using the Game Pack app.

Outcome measures

- Comparison of ratings on digital assessments to progression to cognitive and behavioral endpoints, e.g., changes on the Clinical Dementia Rating (CDR) scale or on the Neuropsychiatric Inventory (NPI).
- Assessments of barriers to technology adherence (e.g., ease of use).
- Assessment of ability of refinements to resolve barriers to technology use.

Opportunities

Technology development in ADRD: Other MADRC/MAITC investigators will be able to use the technology-ready cohort to test novel technologies & methods.

Data Sharing: Data from this work will be made available via open access data sharing with other MADRC/MassAITC investigators, with NACC and NACDA.

Research applications: The programs tested may be used as biomarkers in clinical trials in ADRD.

Acknowledgements

This work is supported by an MassAITC pilot grant through theNational Institute on Aging grant P30AG073107.

#14

Moving Forward in HART Design: Content Validity

Julie Faieta, PhD, MOT, OTR/L[1], Caleb Moon, BS[1], Haomin Hu, MS[2], Yong K. Choi, PhD MPH[2]

1 Rehabilitation Science and Technology, University of Pittsburgh
2 Health Information Management, University of Pittsburgh

Health App Review Tool (HART)

- Designed to characterize the features of apps and then match these features to the needs and abilities of those affected by Alzheimer's Disease and Related Dementias (ADRD).
- The HART is intended to be a low-burden tool that aids those affected by ADRD who are experiencing barriers to initial adoption or sustained health app use.
- Anticipated to impact the clinical recommendation, selection, uptake, and use of health and function supporting apps within ADRD and ADRD caregiver community.

Objective: To develop a refined HART interface (mobile and web-based), finalize the matching algorithm, and incorporate the algorithm into a seamless back-end integration

Setting

- Web-based portal (mobile screens compatible); community setting

Design

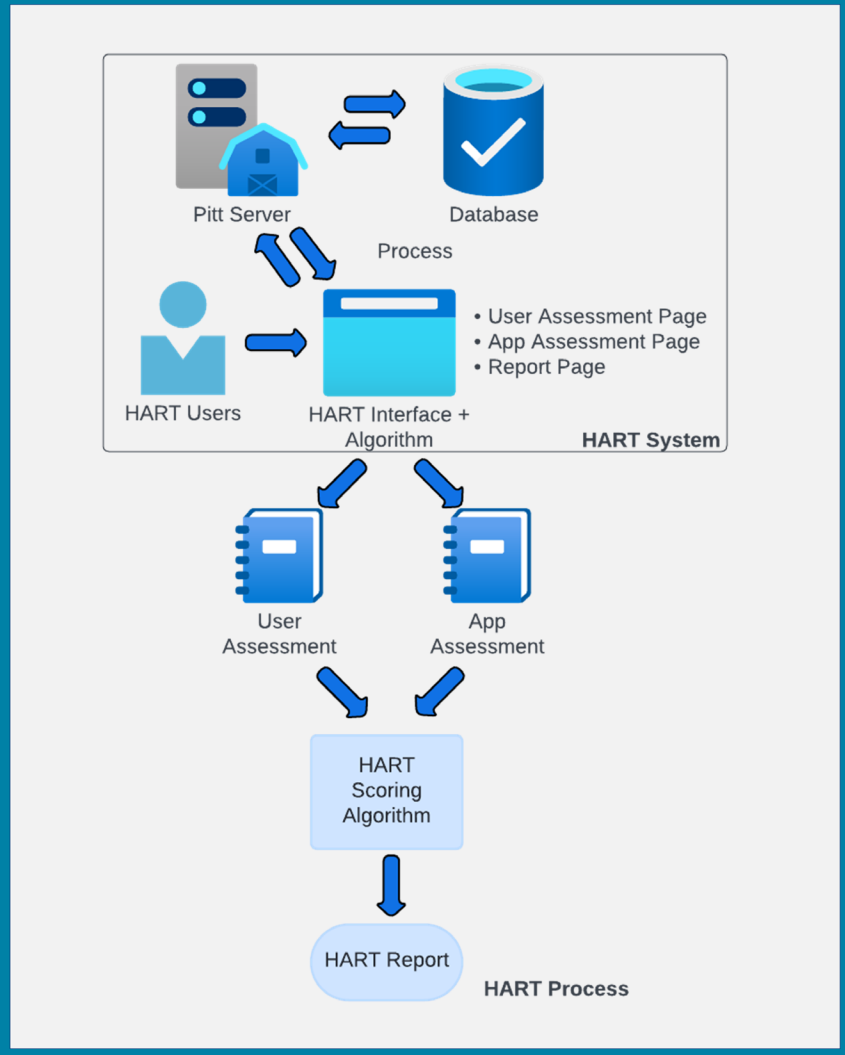
- Human centered design approach

Methods

The digital HART system consists of three parts: 1) **Web Portal (mobile screens compatible)** for the user interface; 2) **Data Server** for facilitating communication between the interface and the database; and 3) **Database** for storing assessment and report data.

University of Pittsburgh

Implementation of the digital HART assessment requires integrating the scoring algorithm into the report generation process



Methods Continued...

The **prototype design and implementation process** includes:

- Designed and implemented user interfaces
  - Configuration and account authorization
  - Assessment pages (User, App)
  - Report
- Translated the HART scoring algorithm from SAS into web programming
- Programmed the system workflow to generate the HART reports

Expected Deliverables

This development aim will result in a dedicated HART interface curated by a co-design process with a stakeholder advisory group. The scoring algorithm will be integrated such that the match score is displayed upon completion of the HART. Availability of the HART is anticipated to maximize the utilization of impactful health technologies, enabling better disease management and higher quality of life for those with ADRD and their caregivers.

Next Steps

Our team is preparing to conduct 4 to 6 co-design workshops with our stakeholder advisory panel, comprising individuals experiencing ADRD or those providing care to a family member with ADRD. Starting with our preliminary webapp interface, our goal is to refine the HART interface through a dynamic process of 'ideation→design→ evaluation.' This approach will lead to a refined design prototype, establishing a solid foundation for the development of the HART WebApp within a concentrated 4-week development sprint.

References

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3. Désormeaux-Moreau M, Michel CM, Vallières M, et al. Mobile Apps to Support Family Caregivers of People With Alzheimer Disease and Related Dementias in Managing Disruptive Behaviors: Qualitative Study With Users Embedded in a Scoping Review. *JMIR Aging*. 2021;4(2):e21808. doi:10.2196/21808
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#15

Speck: A Sensor For Healthier Lighting

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Blue Iris Labs
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BLUE IRIS LABS

MassAITC
Massachusetts AI and Technology Center
for Connected Care in Aging & Alzheimer's Disease

Does getting "bright days and dark nights" result in a measurable improvement in sleep quality?

Background

Circadian disruptions and sleep irregularity are associated with increased mortality, dementia, and a host of other health issues. As we age, so does our circadian system, and studies indicate that 40-70% of the elderly population suffers from chronic sleep disturbances. Light is the primary regulator of our circadian rhythm, regulating the secretion of melatonin. The ways light interacts with our circadian system is affected by the full spectrum of light throughout the day.

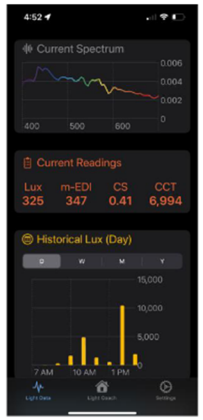
Goals

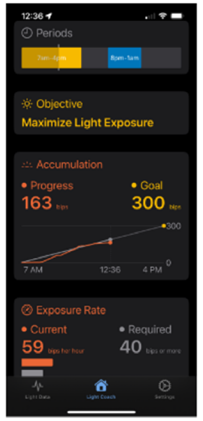
Our goal is to help people better understand their lighting exposure and how to use that data to better regulate their circadian rhythms and improve their sleep quality.

Speck: A Circadian Lighting Sensing System

The Speck sensor is a compact full spectrum lighting sensor. Traditional compact lighting sensors typically only measure brightness or RGB lighting. Full spectrum sensing allows the Speck to measure circadian lighting metrics such as circadian stimulus (CS) and melanopic equivalent daylight illuminance (mEDI). Unlike traditional lighting metrics which measure our visual perception of light, CS and mEDI measure how lighting affects our circadian system. The Speck sensor is accompanied by an iPhone app and web portal, and we have both a BLE version and an openThread mesh networking version depending on user needs.

Our system has been used by researchers as both wearable and stationary sensors. Most recently Pacific Northwest National Laboratory (PNNL) published a study using our sensor to track Well Building Standard compliance in office and factory settings.

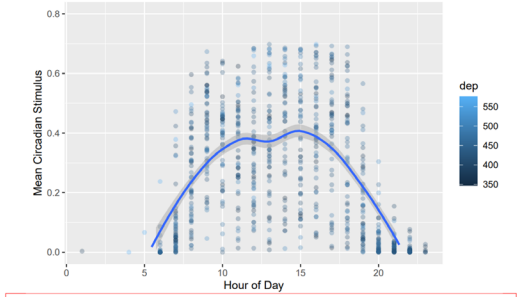




Milestones and User Study

Our pilot study will be validating a study design to use Specks to measure light exposure, and surveys and Apple watches to measure sleep and other relevant factors. Our IRB approval is pending, and we plan to do the study in the next few months with 15-20 participants.

We have been doing internal testing with the Speck and iPhone App to validate our system stability.



We thank the NIH and MassAITC for the National Institute on Aging grant P30AG073107. Previous development on the Speck has also been funded in part by NIA grant 5R44AG060857-06.

#16

DECREASING RISK OF FALLS VIA COMPUTER VISION & AI DRIVEN FUNCTIONAL ASSESSMENTS

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MassAITC AD/ADRD Focus Pilot Core

MassAITC
Massachusetts AI and Technology Center for Connected Care in Aging & Alzheimer's Disease

Background

- The prevalence of falls is over 25% among Americans aged 65+, with Alzheimer's Disease (AD) and Alzheimer's Disease-Related Dementia (ADRD) patients facing double to threefold higher risks (1). This leads to 3 million hospital treatments for fall-related injuries, premature deaths, and exceeds $50 billion in healthcare costs annually, underscoring the need for frequent and accessible in-home assessments (2).
- Addison, is a 3D avatar experience delivered on RGB camera equipped tablet hardware capable of real-world delivery needed fall risk screening.
- Electronic Caregiver has 10 years of human subject research experience around deploying algorithms for human motion.


Infrastructure and Security


Diversity of Need


Delivery at Scale

- Leverages Addison, coupled with Intel's pose estimation technology to perform at-home physical assessments.
- To be delivered via developing feature, called **Functional Assessment in the Home (FAITH)**, aims to detect fall risks early and enhance care for Alzheimer's and related dementia patients.

Aims

System Evaluation

- Assess AC's computer vision accuracy against a gold-standard infrared motion system during SPPB-A AD/ADRD patients.

Algorithm Enhancement

- Enhance model accuracy using synchronized data to refine pose estimation during functional movements for real-world application.

Pilot Project Highlights

Inclusion Criteria:

- 20 participants with AD/ADRD capable of on-campus visits and qualifying TICS and MOCA scores.

Protocol Overview:

- Use of a single tablet-based Addison unit for data collection.
- Collaborative data collection by ECG and UMass leveraging Addison Care and motion capture technology.

Assessments for Data Collection:

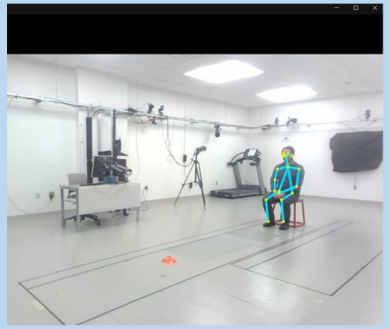
- Johns Hopkins Fall Risk Assessment Tool (JHFRAT).
- Short Physical Performance Battery Assessment (SPPB-A).

Data Analysis:

- Analyze patient responses and clinician entries from JHFRAT.
- Assess [x,y] and [x,y,z] spatiotemporal data for patient movements during SPPB-A assessments from both the Addison unit and UMass MoCap lab.

Expected Outcomes and Anticipated Impacts

- Outcomes from this pilot are to validate and tune an algorithm to be used to measure functional assessments from the deployed Addison Care RGB camera technology.
- By evaluating and enhancing the algorithm of **FAITH**, this initiative is set to enhance patient safety and potentially decrease healthcare costs related to fall injuries in the elderly and AD/ADRD patients.



Acknowledgements: This work is funded in part by National Institute on Aging grant P30AG073107

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#17

EZ-Aware: Digital Twin for wearable-enabled, AI-supported assessment of cognitive impairment

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** Rhode Island Hospital, Providence, RI
*** Brown University, Providence, RI
JH AITC [AD/ADRD or Aging] Focus Pilot Core

Problem

13.8M diagnosed with Alzheimer's Disease (AD) by 2050 [1]

$1T cost to care for AD and related dementia [2]

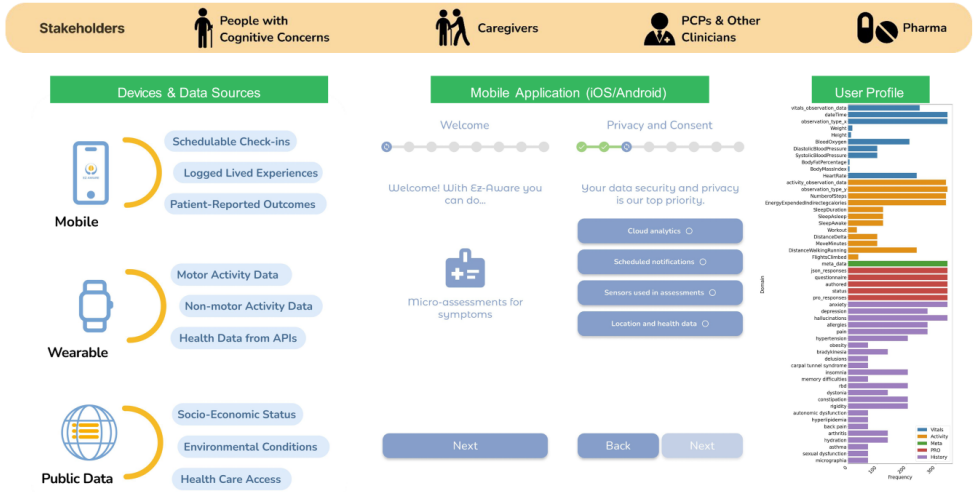
15% of MCI patients progress to dementia in a year [1]

Lack of data and efficient tools to collect and detect cognitive impairment in diverse populations at a large scale

Aim

To design a digital health application, EZ-Aware that can bring cognitive assessments into everyday environments and offer following values to end-users:

Reliable and engaging health experience
Clinically proven, comprehensive tests
Deployable at clinics, community, and homes
Multiple language support for cultural diversity



Digital Cognitive Screening

NIH/NIA STTR Phase I

The STTR phase I project (2021-23) developed and tested a digital cognitive screening tool designed to accurately identify mild cognitive impairment in older adults.

- 99 participants (Healthy Controls [HC] n=49; Cognitively Impaired [CI] n=50) completed the cognitive screening twice (in one month span).
- The data analysis demonstrated strong test-retest reliability/internal consistency, and evidence of concurrent/construct validity.

Passive Monitoring

NSF SBIR Phase I

The SBIR phase I project (2021-23) focused on developing and testing EZ-Aware, a digital health platform designed to support individuals with Parkinson's Disease (PD) and caregivers.

- We conducted a feasibility study to verify the usability and robustness of the EZ-Aware app in the daily lives of people with PD (n=31) and caregivers (n=14).
- All the participants liked EZ-Aware, with an average usability rating of 4.75/5.

Current Focus

EZ-Aware is currently under developments to bring cognitive assessments into everyday environments.

It incorporates age-friendly, digital interfaces for smartphones (and tablets) delivering periodic micro-assessments (span across several weeks) for various cognitive domains. This provides a robust estimate of cognitive functions.

The EZ-Aware app will be piloted for feasibility in a 6-week in-home study in which 30 participants (15 healthy old adults and 15 with mild cognitive impairment [MCI]) will complete brief cognitive screening assessments, periodic micro-assessments, and collection of daily life functions via smartwatch.

Project Timeline

Aims	Q1	Q2	Q3	Q4
1 Cognitive Micro-Assessment Design				
2 In-Home Pilot Study (N=30)				
3 Digital Twin & Public Datasets				

Citations

1. Alzheimer's Association. 2023 Alzheimer's Disease Facts and Figures. Alzheimers Dement 2023;19(4). DOI 10.1002/alz.13016.
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Acknowledgements

This work is supported by various grant funds including NIH/National Institute on Aging A2Pilot grant (#P30AG073104), NIH/National Institute on Aging STTR Phase I grant (#R41AG074835), and National Science Foundation SBIR Phase I grant (#2136605).

#18

Utilizing the Druid® Impairment App to Assess and Enhance Senior Adults' Driving Performance

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Anuj Pradhan, PhD, Apoorva Hungund, and Melissa Paciulli
Human Performance Lab, UMass/Amherst
MassAITC Aging Focus Pilot Core

MassAITC
Massachusetts AI and Technology Center
for Connected Care in Aging & Alzheimer's Disease

Study Background

Aging adults face multiple difficulties that can impact their driving performance, ranging from stiff joints and slower reaction times to prescription medications and dementia. In a meta-analysis of research on older drivers' self-perceived driving ability, Huang et al. (2020) observed, "As people age, some can recognize and identify these sensory, cognitive, and physical changes by themselves, while others cannot." In addition, they found that "Overall, the majority of studies report that older adults self-perceive their driving abilities to be better/higher than themselves at a younger age, their cohorts, and all other drivers, as well as better/higher than their objective driving ability evaluation."

Study Overview

GOAL: To determine whether the Druid impairment app can predict driving performance and assist with healthy aging.

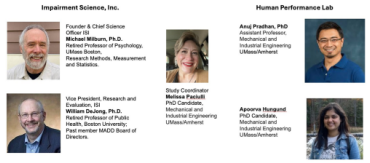
SAMPLE: Recruiting 40 participants aged 65-84

Two aspects of the proposed research:

--Performance on Driving Simulator at UMass/Amherst Human Performance Lab (HPL)

--Performance on Druid impairment measurement app from Impairment Science, Inc.

Project Team



Human Performance Lab

Multiple driving scenarios developed

Measuring multiple aspects of driving performance, including

- Longitudinal and lateral velocity
- Braking force
- Reaction time
- Driving errors
- Visual gaze performance

How Druid Works

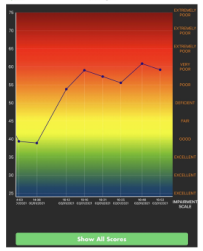
Four Tasks (3 require divided attention), measuring:
- Reaction Time
- Decision Making
- Object Tracking--Hand/Eye Coordination
- Time Estimation
- Balance

Two versions: Rapid (1-minute) and Benchmark (3 minutes)

Available for all iOS or Android platforms (phones and tablets)

Using propriety software, DRUID® calculates a

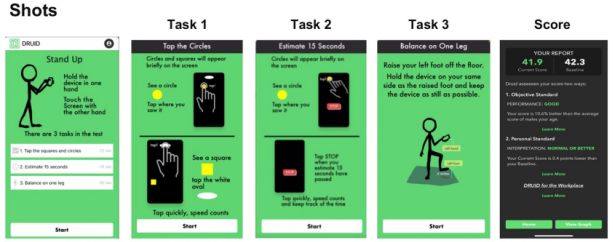
Total Impairment Score. Range 25-75; 55 ≈ BrAC = .08



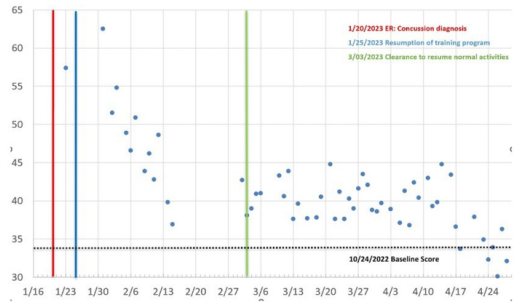
DRUID® Graphic Results Display

Higher score = Greater impairment

Screen Shots



Case study of Druid's sensitivity tracking impairment after and during recovery from concussion due to a fall



Multiple published, peer-reviewed validation studies show Druid's sensitivity in measuring cognitive-motor performance after consuming alcohol or cannabis

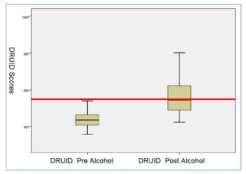
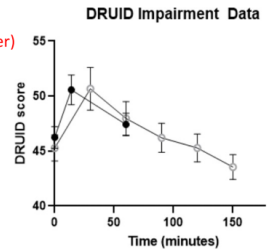


Figure 6. Boxplot of the medians for the DRUID® Baseline scores vs. DRUID® intoxicated scores beyond BAC 0.08%

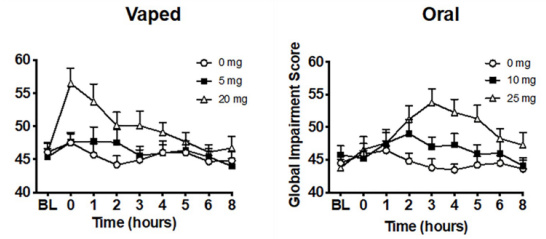
Richman, J. E., & May, S. (2019). An investigation of the Druid® smartphone/tablet app as a rapid screening assessment for cognitive and psychomotor impairment associated with alcohol intoxication. *Vision Development Rehabilitation, 5*, 31-42.

Frequent cannabis users (UC Boulder)



Karoly HC, Milburn MA, Brooks-Russell A, Brown M, Streufert J, Bryan AD, Lovrich NP, DeJong W, Bidwell LC (2020). Effects of high-potency cannabis on psychomotor performance in frequent cannabis users, *Cannabis and Cannabinoid Research* X:X, 1–9, DOI: 10.1089/can.2020.0048.

Infrequent cannabis users (Johns Hopkins)



Spindle TR, Martin E, Grabenauer M, Woodward T, Milburn MA, Vandrey R. (*In press*). Assessment of Cognitive and Psychomotor Impairment, Subjective Effects, and Blood THC Concentrations Following Acute Administration of Oral and Vaporized Cannabis. *Journal of Psychopharmacology.*

Conclusions

--Druid is a reliable and highly sensitive measure of cognitive-motor performance and impairment

--We anticipate that this study will demonstrate that Druid can predict driving performance and a variety of errors made while using the HPL driving simulator in a senior population

This research is supported by National Institute on Aging grant P30AG073107.

#19

Prevention of Patch Poisoning in Elderly Alzheimer's Patients

PennAITech AD/ADRD Focus Pilot Core

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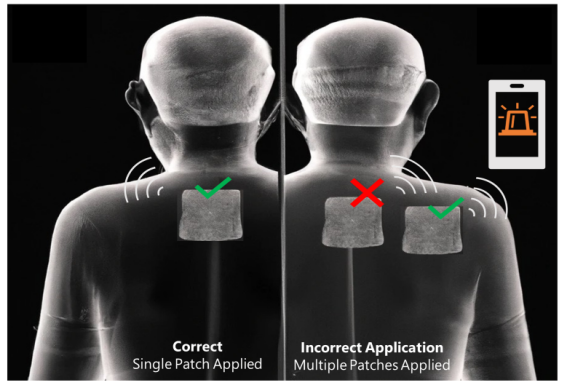
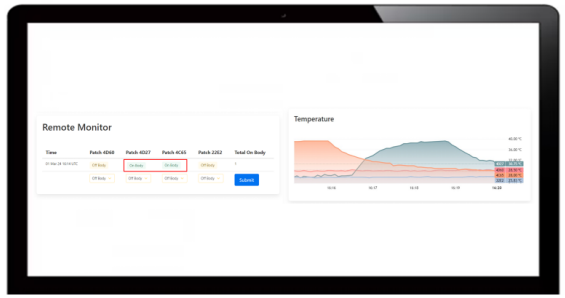
Vaaji LLC, Los Angeles, CA

Developing a smart transdermal therapeutic patch and AI-enabled monitoring platform to improve safety of patients with Alzheimer's disease



Transdermal Therapeutic Patch Application



Monitoring Platform

Project Overview

Background

The Need:
Transdermal medicine patch application errors are common and are associated with serious consequences.

- Per the Federal Adverse Event Reporting System, **>7000 serious events (including fatalities)** have been reported with transdermal rivastigmine patches used in the treatment of Alzheimer's Disease (AD).
- Similar reports of serious incidents or fatalities involve fentanyl, clonidine, scopolamine, and other patches. (Institute of Safe Medicine Practices, 2021)

The Opportunity:

- No method currently exists to monitor therapeutic patch use.
- Early detection and intervention can prevent adverse outcomes.

Key Benefits:

- Reduce morbidity and mortality.
- Increase caregiver support.
- Facilitate healthy aging at home.

Objectives and Methodology

Primary Study Outcome:
The primary outcome variable will be the degree to which the information derived from the remote monitoring portal accurately reflects the number of patches on a participant in the Home Health Lab as noted by the site research personnel.

Clinical Study Design:

- 50 healthy volunteers
- Up to 3 placebo patches per volunteer
- Scripted activities in home-like environment
- Real-time monitoring via cloud data platform
- Compare remote monitor data with site observations

Exploratory Hardware Research	Clinical Study Protocol Development and IRB Application	Clinical Study Hardware Selection	Data Platform and Infrastructure Development	**Clinical Study**	Data Analysis and Reporting
September 2023	November 2023	December 2023	January - April 2024	May - August 2024	October 2024

Progress and Ongoing Activities

Hardware:

- ✓ Ongoing exploration of active and passive RFID and Bluetooth tags
  - Core requirements: size < 2x2", signaling distance while on body >6ft
  - Three different types of tags met the core requirements after testing
- ✓ Selected a disposable, low-cost, BLE signaling tag with non-toxic battery
  - The chosen tag surpasses size, range, battery life, ease of integration, and data consistency requirements

Data and Infrastructure:

- Remote monitoring capabilities and data collection for study purposes
- Site feasibility assessment

Key Milestones

- **Study protocol approved by IRB - January 2024**
- Recruitment materials have been finalized
- Data collection protocol and instruments moved to production

Conclusion

A successful study will provide a strong proof-of-concept for developing a pioneering, FDA approved smart transdermal therapeutic(s) aiming to substantially enhance the safety of patients with Alzheimer's and facilitate healthy aging at home.

The project described is supported by the National Institute on Aging of the National Institutes of Health under Award Number P30AG073105. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

Contact: tushar@vaaji.io

LEARN MORE!

#20

Predicting Fall Risk in Older Adults Using Machine Learning

RM Patterson*, J Knebl, KG Fulda, K Camp, F Zhang, M Albert
JH AITC [Aging] Focus Pilot Core

Purpose

Use point of care data to create an algorithm to predict falls and provide real time feedback to clinicians.

Background

Falls are a significant health problem

- 684,000 fall-related deaths in older adults, annually
- 80% are in low to middle income countries.
- Results in more years lived with disability and a decrease in life expectancy

The cause is complex

- Health conditions
- Body structure/function
- Environment
- Personal factors

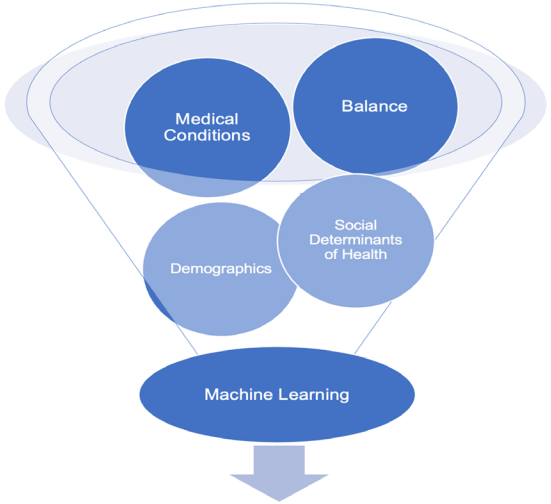
Pilot Project Highlights

Methods:

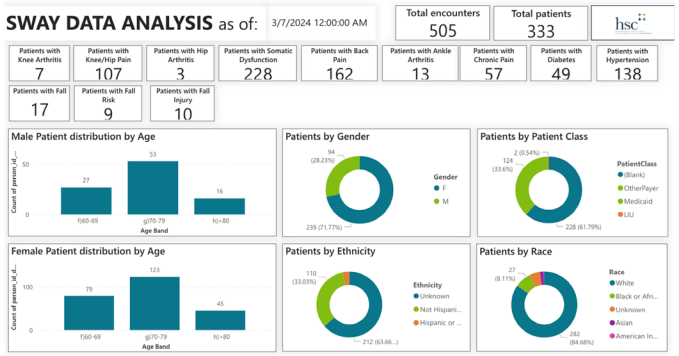
Balance data with eyes open and closed is collected while performing intake vitals in the HSC clinic for older adults on all patients (2-minute protocol using a Bertec Force plate).

Milestones:

- Clinical - Collect 1000 encounters
- Update the Power Bi dashboard for viewing
- ML – **Use an unsupervised autoencoder network** to learn statistical relationships in patient demographics, medical comorbidities, balance variables, and falls.



Fall Risk at Point of Care



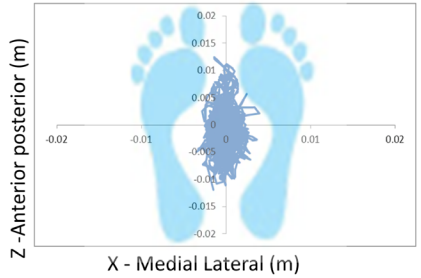
Current Sway Dashboard filtered for patients 65 and older

Acknowledgements

Funds to support this AITC study were provided by the Johns Hopkins University AITC under award number P30AG073104.

Balance is an ability to maintain the line of gravity (vertical line from center of mass) of a body within the base of support with minimal postural sway.

Sway is the movement of the center of gravity even when a person is standing still.



Quiet standing sway plot

Conclusions

- Managing data from dashboard & EMR
- Integrating data into clinical workflow
- Correlating sway data with individual EMR data (i.e. health conditions, demographics)
- Developing advanced algorithms for prediction
- Planning Core Interactions specifically
  - Stakeholder Engagement Core
  - Technology Identification and Training Core
  - Networking and Engagement Core

#21

Towards Objective Detection of Neuropsychiatric Symptoms using Ambient Intelligence

Narayan Schütz*, Christine E. Gould, Silvia Tee, Feng Vankee Lin, Ehsan Adeli
Stanford University
JH AITC AD/ADRD Focus Pilot Core

MOTIVATION

- Neuropsychiatric Symptoms (**NPS**), such as **agitation** or **depression** are commonly overlooked in older adults.
- NPS are common **early manifestations** of **neurodegeneration** (prevalence of up to 90% in mild cognitive impairment).
- NPS **negatively** affect the **quality of life** of both older adults themselves as well as their caregivers.
- **Current assessment** is based on clinician and caregiver-reported outcomes, thus often **subjective**, **lacking detail**, and limited in **frequency**.

OBJECTIVES

I. **Collect** clinical and at-home ambient sensing **data** from patients with NPS

II. **Detect** select NPS **indicators** using state-of-the-art computer vision (CV) **algorithms**

III. **Build** a clinician **interface** to let them succinctly access key NPS indicators

METHODS

(1) Collect Data

Study Population

20 Participants, Aged **65+**

10 with reported **agitation**

10 with reported **mood disorders**

Study Design

Observational **Pilot** Study

3-Month Duration

Audio-Visual Ambient Sensor in participant's **kitchen** and **dining** area

Clinical **Assessments** of NPS and cognition

Outcomes

Clinical Assessments:
▶ Mild Behavioral Impairment Checklist (**MBI-C**)
Schedule: ***Beginning*** - ***End***

▶ Neuropsychiatric Inventory (**NPI-Q**)
Schedule: ***Beginning*** - ***End***

▶ Cognition (based on existing health records)

Ambient Sensors:

• 30 FPS
• 720p

Video

• 16 kHz
• PCM

Ambient Audio

Schedule: Continuously

(2) Detect NPS

Exemplary NPS Indicators

Evaluation

Video → Human Poses Through Time

Video & Audio → Activities of Daily Living

Video & Audio → Facial Expressions and Emotions

Motor
- Wandering
- Fidgeting
- Shaking/ Tremors
- Physical Activity
- ...

Emotion
- Anger (towards self, others, or objects)
- Sadness
- ...

Behavior
- Appetite/ Eating
- Social Isolation
- Inadequate Clothing
- ...

Correlate NPS Indicators with MBI-C and NPI-Q

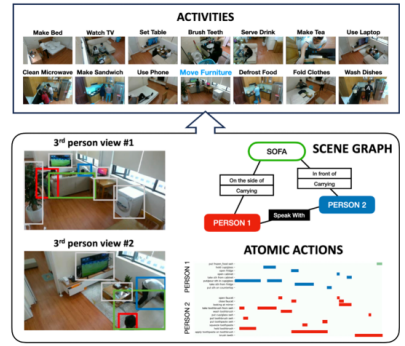
Indicators Differentiate Participants with Agitation vs Mood Disturbances

(3) Build Clinician Interface

Survey Clinicians → Identify Most Useful Extracted NPS Information → Develop a, possibly Large Multimodal Model Powered, Physician Interface

CV for detecting ADL/NPS

Few-shot detection of activities that correlate with NPS.



- Home Action Genome (homeactiongenome.org)
- Multi-Object Multi-Actor Activity Parsing (moma.stanford.edu)

CONCLUSION

- **IRB** is approved; recruitment has started; identified 6 participants so far.
- Immediate **next steps** include (1) data collection, (2) running a clinician survey on what items to include in the clinician survey. (3) Implementing a prototype.
- This system may lead to the discovery of novel **digital biomarkers** that can be continuously tracked through time.

ACKNOWLEDGEMENT

- JH AITC: National Institute on Aging grant P30AG073104.
- Stanford School of Medicine, Department of Psychiatry and Behavioral Sciences, Jaswa Innovator Award.

#22

FairAD
Fair and Interpretable Alzheimer's Prediction Approaches

Fairness and Robust Interpretability of Prediction Approaches for Aging and Alzheimer's Disease

Li Shen[1,*], Kazi Noshin[2], Victoria Lu[2], Bojian Hou[1], Weiqing He[1], Mary Regina Boland[3], Carol Manning[2], Aidong Zhang[2]
[1]Univ. of Pennsylvania, [2]Univ. of Virginia, [3]Saint Vincent College
PennAITech AD/ADRD Focus Pilot Core

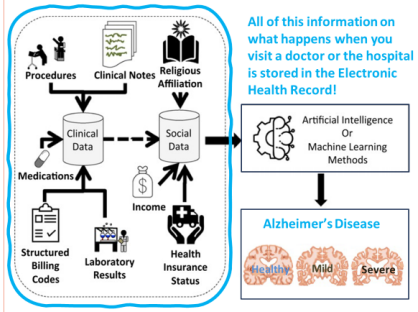
PennAITech

Introduction

- Opportunity of EHRs to diagnose AD/ADRD
- EHR-based ML methods that are fair, robust and interpretable solutions for current diagnosis and prediction of the AD/ADRD risk in future

Objective

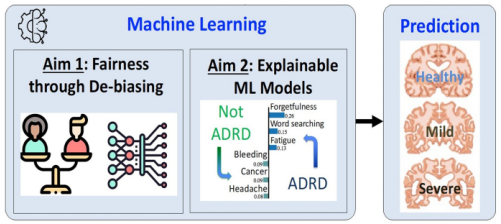
- Leveraging EHR data in predicting and classifying AD/ADRD
- Defense against Racial / Ethnic Disparities
- Clinical Interpretability via trustworthy AI/ML Methods



- We will take this clinical data and build fair / interpretable models to predict AD severity

Method

- Integration of Debiasing Techniques
- Development of Explainable ML Methods
- Improvement of Human-Centered AI Technologies



- Fairness learning: bilevel optimization to remove bias.
- Train global / local models in upper / lower levels, respectively.
  - Lower level: train local models for each group using KL divergence as regularization to restrict the local models close to the global model.
  - Upper level, train a global model on the entire data and use KL divergence to make it close to all the local models.
  - KL divergence btw models: Bayesian method to transform model parameters into distributions + MC sampling to create specific models.

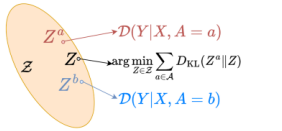
$$\text{Upper Level} \quad \min_{f\in\mathcal{F}} \frac{1}{|\mathcal{A}|}\sum_{a\in\mathcal{A}} \mathrm{KL}(f^a\|f)$$

$$\text{Lower Level} \quad \text{s.t.} \quad f^a = \arg\min_{f^a\in\mathcal{F}} \ell_{CE}(y_{[a]}, \mathbf{x}_{[a]}, f^a) + \alpha \mathrm{KL}(f^a\|f), \forall a \in \mathcal{A}$$

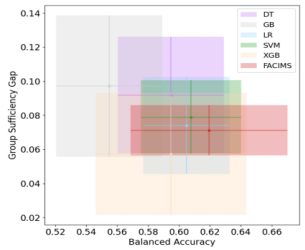
Bayesian

$$\text{Upper Level} \quad \min_{Z\in\mathcal{Z}} \frac{1}{|\mathcal{A}|}\sum_{a\in\mathcal{A}} \mathrm{KL}(Z^a\|Z)$$

$$\text{Lower Level} \quad \text{s.t.} \quad f^a = \arg\min_{f^a\in\mathcal{A}} \mathbb{E}_{f^a\sim Z^a} \ell_{CE}(y_{[a]}, \mathbf{x}_{[a]}, f^a) + \alpha \mathrm{KL}(Z^a\|Z), \forall a \in \mathcal{A}$$



Z is the distribution of global model, $Z^!$ and Z^* are the local models for group a and b



Boxplot comparing balanced accuracy and group sufficiency gap for three real datasets with 5 repeats. The mean is represented by the middle of each box, while the box width represents twice the standard deviation. Better performance is indicated by boxes located towards the bottom right (higher BACC and lower GSG). The models are Support Vector Machines (SVM), Logistic Regression (LR), Gradient Boost (GB), XGBoost (XGB), Decision Tree (DT), and FACIMS.

Method	Balanced Accuracy ↑	Sufficiency Gap ↓
ANN	0.5499±0.0521	0.0995±0.0424
DT	0.5948±0.0343	0.0919±0.0341
GB	0.5548±0.0343	0.0972±0.0415
LGB	0.6053±0.0366	0.1454±0.0458
LR	0.6048±0.0279	0.0740±0.0284
NB	<u>0.6096±0.0283</u>	0.2030±0.0786
RF	0.6037±0.0300	0.1040±0.0443
SVM	0.6078±0.0324	0.0789±0.0217
XGB	0.5948±0.0488	**0.0573±0.0357**
FACIMS	**0.6195±0.0508**	<u>0.0712±0.0148</u>

Comparative evaluation of ML algorithms based on average balanced accuracy and average group sufficiency gap metrics. Each entry shows the mean and standard deviation (mean±std) of performance scores across multiple trials. The best one is bold and second best one is underlined.

Timeline and Milestones

Table 1. Timeline and Milestones		Q1	Q2	Q3	Q4
Aim 1. Enhance Fairness through De-biasing	Data Instance Perspective	x			
	Feature Perspective	x	x		
Aim 2. Explainable ML models	Post Hoc Interpretation		x	x	
	Self-Supervised Interpretation		x	x	
Evaluate methods, submit papers, disseminate code & results				x	x

Participation Information

- Our preliminary PennMedicine data demonstrate that EHRs can be used to identify cohorts of ADRD patients.

	ADRD (N=70,300)	65+ Population (N=1,671,560)	% increase in ADRD
Sex			
Female	54%	53%	+1.89%
Age mean (min, max)	82 (65, 90)	79 (65, 90)	
Race			
White	65%	61%	+6.56%
Black/African American	23%	13%	+76.92%
Asian	2%	2%	0%
Unknown/Other	10%	24%	-58.33%
Ethnicity			
Hispanic	2%	1%	+100%

Anticipated Outcomes

- Algorithms & tools: De-bias EHR datasets → more trustworthy and generalizable for AD/ADRD prediction
- Algorithms & tools: Interpret prediction models → help inform decision making for AD/ADRD.

Acknowledgements. This work is supported by National Institute on Aging grant P30AG073105 (PennAITech)

#23

AI-Supported In-Home Brain Assessments for Older Adults and Persons with Alzheimer's Disease

Jian Shi, MD*, Jacqueline Gong, BA*, Gary Strangman, PhD, Deborah Blacker, MD, PhD, Quan Zhang, PhD
Neural Systems Group Biomedical Engineering Lab | Massachusetts General Hospital / Harvard Medical School
MassAITC AD/ADRD Focus Pilot Core

MassAITC
Massachusetts AI and Technology Center for Connected Care in Aging & Alzheimer's Disease

Background/Introduction/Motivation

- Early and accurate AD diagnosis could save up to $7.9 trillion in medical and care costs, but it can be onerous for older adults to go to the hospital or clinic for regular assessments
- Current clinical AD diagnosis tools—including PET, MRI, cerebrospinal fluid biomarkers—are cumbersome, expensive, or invasive
- *What if a self-deployable 'mobile clinic' device could support AD-relevant, brain-based assessments at home?*

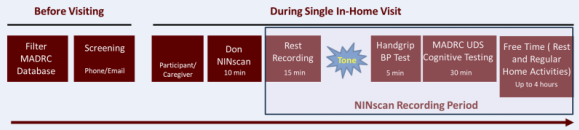
Our Process

1. NINscan Optimization for In-Home Assessment

- Integrate multiple sensing capabilities into one single, easy-to-wear headband

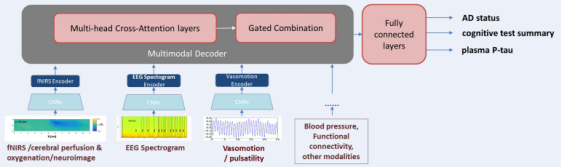
2. Human Subjects Data Collection

- Recruit n=15 AD patients, n=15 cognitively healthy controls
- Collect multivariate neurophysiological data and cognitive status at home



3. AI Model for Current AD/Cognitive Prediction

- Develop cross-attention based, multi-modal deep learning prediction model



Our NINscan Technology

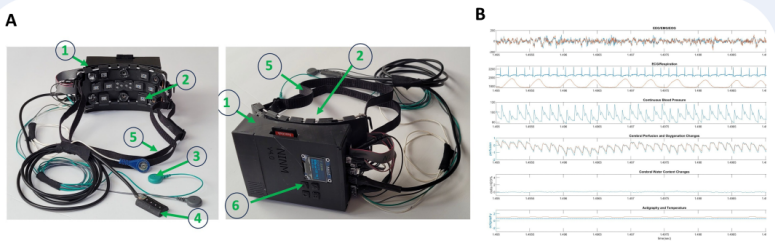


Figure 1 (A) NINscan multimodal vital sign data collection technology. Labels: 1. NINscan recorder 2. Multimodality probes with integrated EEG, NIRS, actigraphy and temperature-based sensors and adaptive shape 3. ECG electrodes 4. Tonometry based noninvasive blood pressure sensor 5. Elastic headband 6. Event buttons and screen **(B)** Sample NINscan dataset.

Key requirements for application in older adults:
*Easy-to-use *Meaningful *Cost-effective

- Our self-developed **NINscan** is a battery-powered wearable neuroimaging and vital sign monitoring device
- NINscan simultaneously measures numerous neural and vascular physiological features during rest and daily activities
- We expect to provide comprehensive brain assessments and AD related diagnosis at home

Sensor	AD-relevant variables
Near-infrared spectroscopy (NIRS)	Regional changes in cortical hemoglobin (O_2Hb, HHb, HbT) and water* concentrations •Cerebrovascular volume pulsatility & vasomotion •Tissue oxygenation & functional brain activation •Cerebral perfusion •Inter-regional functional connectivity •Tissue water percentage changes & CSF pulsatility
Continuous blood pressure (STAT)	Head-level cuffless blood pressure changes •Blood pressure pulsatility changes •Cerebral autoregulation (combined with NIRS)
EEG	Brain electrical activity •Resting-state & functional activity •Sleep staging
ECG	Cardiac monitoring
Respiration	Respiration rate/depth
Accelerometer / Gyrometer	Tri-axial linear/angular acceleration of head motion •actigraphy

Future Directions

Recruitment & Home Monitoring
15 AD and 15 controls from the Longitudinal Cohort within MGH's Massachusetts Alzheimer's Disease Research Center's (MADRC)

Develop an AI model
- Transformer-based predictor: data from NINscan systems as inputs
- Extract high-level semantic knowledge
- Establish correlations between different data types in the cross-attention-based decoder
- Combine different data types in the decoder by gated mechanism.
- Simultaneously predict the target AD status/cognitive test scores/plasma Tau using multitask fully connected layers

Additional Applications
- *Cardiovascular disease (CVD)* - NINscan can also monitor numerous parameters relevant to CVD (continuous blood pressure, vasomotion and pulsatility/distensibility, cerebral autoregulation).
- *Sleep assessment* – Sleep is critical to health, but often disrupted in aging populations. NINscan has been demonstrated for self-deployed polysomnography use with NASA.

Acknowledgements
National Institute on Aging
Grant P30AG073107

#24

Expanding a Multimodal VR Fitness Platform to Remotely Assess, Monitor, and Report Cognitive and Physical Function for Older Adults

Jennifer Stamps, PhD., Kyle Rand, Thomas Neumann, Erin Naffziger,PhD., Yuval Rosen
Rendever, Inc.
MassAITC [AD/ADRD *or* Aging] Focus Pilot Core

RENDEVER
expanding worlds.

MassAITC
Massachusetts AI and Technology Center
for Connected Care in Aging & Alzheimer's Disease

Background

Surgeon General 2023 Advisory on the "public health crisis of loneliness, isolation, and lack of connection" [1]

- **Social isolation: 30% increase in mortality rates, 50% increase in risk of dementia, and ~30% increase in stroke and cardiovascular disease -** 3 major causes of loss of function for older adults.

National Academy of Sciences 2017 summary report on the data **to delay or prevent cognitive decline** in aging found encouraging results for blood pressure medication and **two *behavioral* interventions: Exercise & Cognitive training** [2]

- Exercise = effective strategy for
  - maintaining independence
  - preventing/reducing cognitive & physical disability
  - reducing healthcare burden of aging population
- BUT... It's not fun. Low compliance limits it as a widespread strategy.

RendeverFit® is the first VR exergaming platform that combines physical, cognitive, and social stimulation.

Research in VR exergaming has demonstrated the potential efficacy of improving physical and cognitive function and suggest potential as a digital diagnostic biomarker.

RendeverFit® Results from initial pilot study with FrontPorch and UCS [3]

2 sessions (30 min)/wk, 4 weeks, 18 participants, avg age: 76.3

- **Significant improvements in all 3 physical function assessments:**
  - 78% of participants sig improved on the TUG test ($F(1,17) = 4.4$, $p=.05$)
  - 94% of participants sig improved on TUG Manual ($F(1,17) = 39.4$, $p<.001$)
  - 89% of participants sig improve on TUG Cognitive ($F(1,17) = 17.4$, $p<.001$)
- 9% average increase in movement speed
- **Physical Health, Abilities and Mobility index ($\alpha = .95$) improved, $p = 0.01$**
- 48% decrease in fall anxiety
- 44% decrease in pain interfering in daily life/sleep
- 33% decrease in loneliness
- 36% increase in the trust of others they exercised with in RendeverFit®
- **100% of users thought RendeverFit was fun**
- 94.1% of users had a positive composite of user experience ratings

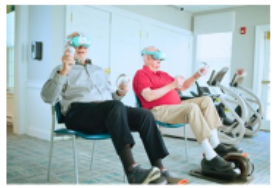
67.7 average rating for how much they liked exercising with RendeverFit
scale: GHIS, -100 to +100 (most pleasurable event of their entire life)

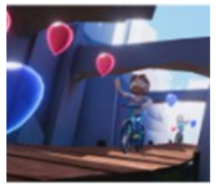
Objective

To develop accurate, unbiased ML algorithms using the passively collected data from RendeverFit® to assess and remotely monitor cognitive and physical function of older adults at home.

Methods

- **30 older adults** with cognitive impairment currently receiving physical therapy + **30 live-in family caregivers living with them**
  - **decentralized recruitment across US via Citruslabs app**
- **Use RendeverFit® for their PT-prescribed exercise for 6 months**
  - uncompliant dyads will be replaced with new recruited dyad
- **Collect daily, weekly, and quarterly standardized assessments** of cognitive and physical function
  - **Cognitive health**: MoCA, Mini-cog, reaction time test
  - **Physical function**: time-up and go (TUG), TUG-manual, TUG-cognitive, 4-stage balance test, functional reach test, fall anxiety, ADLs, Garmin vivosmart 5 watch data
  - **Pain**: acute pain, brief pain inventory
  - **Mental health**: depression (PHQ-8), anxiety (GAD-7), QoL
  - **Caregiver**: Caregiver burden and stress (BakasCOS), Communal coping, relationship closeness
- Collect daily **Garmin VivoSmart 5 watch data**: HR, Sleep, steps, etc





Cycle: Safe, accessible lower body exercise w upper body and cognitive challenge. Bike across the world while popping balloons, race w friends, improve dual-task function, leg exercise increases BDNF [4]

Pong: develop swing, match colored targets Lifelong table tennis players have greater hiippocampal volume, less cognitive decline than peers. Other documented benefits: balance, core strength, reflexes [5-6-7]

Paint: Up to 10 people can move around in a 360 virtual canvas to create a masterpiece , mixing colors, choosing brushes/effects, tool use. Divergent thinking, strengthened frontal and associative cortical connections [8]

Outcome Measures

- **Technology acceptance:** system usability score, tech acceptance metric, RendeverFit usage data
- **Novel outcomes** from feature extraction from incoming data streams, **ML build, for example**
  - **6DoF Positional Tracking:** balance, rigidity
  - **Eye Tracking:** target tracking and latency, horizontal and vertical saccades, attention
  - **Face Tracking:** mask-like face, appropriate emotional valence, facial asymmetry paresis/ droop
  - **Hand Tracking:** reach, tremor, cogwheel rigidity, dyskinesia, reaction time, range of motion
  - **RendeverFit Data:**
    - **Cycle:** dual-task score, single-task score, balloons pop accuracy, distance traveled, speed, cadence
    - **Pong:** accuracy, score, paddle collision speed, difficulty, off/on target hits, paddle distance traveled, swing depth, spin percentage, total hits
    - **Paint:** distance moved, range of motion, # brushstrokes, tools used, time spent, artwork created
- ML Output Score: **physical function** measure & **cognitive function** measure interpretable by all stakeholders

Implications

Offer a fun, social exercise option accessible for people along the whole spectrum of cognitive and physical ability

Develop digital biomarkers to remotely monitor the health of older adults while they're having fun exercising at home

- Empower caregiver decision-making, support CG health
- Reduce time to treatment w remote monitoring
- Provide nonpharmacological solution for pain

Provide requested digital therapeutic device for PT maintenance program

Acknowledgments

Thank you to the **MassAITC** for funding this research with the **National Institute on Aging** (P30AG073107). This work was also funded in part by the National Academy of Medicine's Healthy Longevity Global Competition Catalyst Award.

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#25

UC San Diego

Non-Intrusive, Fine-Grained In-Home Daily Activity Transcription for Alzheimer's Monitoring

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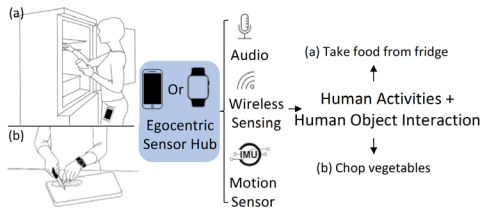
PennAITech

Abstract

- **Background:** Monitoring in-home activities of daily living (ADL) is essential for early detection of AD.
- **Goal:** Using on-body smartphone/smartwatch as an egocentric sensor hub to sense and transcribe a subject's ADLs.
- **Motivation**
  - Self-reported assessment is time-consuming, error-prone, and requires strict patient compliance.
  - Cameras-based solutions are often prohibited due to privacy concerns.
- **Key Hypothesis:** non-visual multi-sensor fusion methods can be empowered by a data-driven model to achieve near-vision precision.



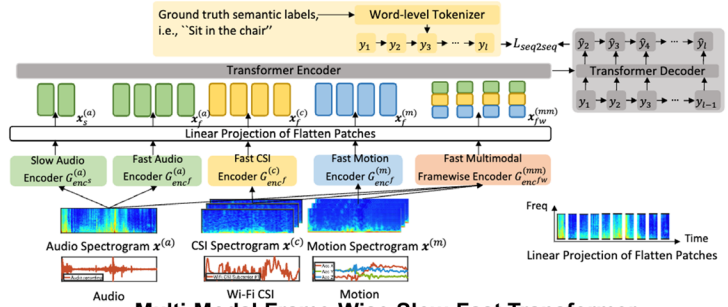
Goal

- Open-ended, fine-grained body motion + human-object interactions:
  - Higher accuracy; - Extensibility for few-shot behaviors with limited labels;
  - Generalization across different behaviors, users and environments

Challenges and Solutions Highlights

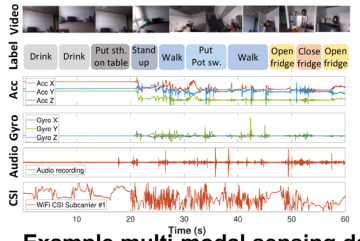
Fusing heterogeneous multi-modality sensors

- Audio: behaviors with unique sound events;
- Wireless Sensing: coarse-grained full-body behaviors and interactions with the ambient environment;
- Motion Sensor: ambulatory actions of single point



Multi-Modal Frame-Wise Slow-Fast Transformer

Data and annotation scarcity



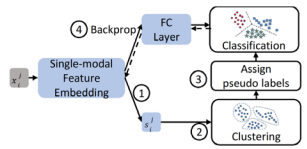
Example multi-modal sensing data

- Overfitting problem
- Lack of generalization

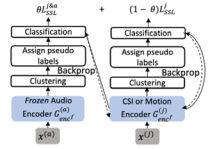
Data Collection Scenario

Self-supervised multi-modal feature representation

- Self-Supervised Deep Clustering
- Knowledge distillation from external audio datasets



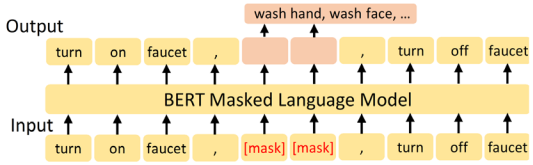
Single-modal deep clustering



Cross-modal deep clustering

Semantic transcription of behaviors

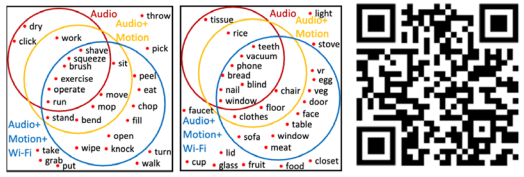
- Refine the annotations to match the sensing capabilities of sensors
- Fine-tune the language model to learn the contextual reasoning



Contextual language models

Results and Future Work

- Open-sourced dataset and benchmark
- 72.5% top-1 and 90.8% top-5 mAP for recognizing 105 human behaviors, 49 object interactions, and 54 actions.
- Significant improvement in generalization and extensibility for unseen environments users, and behaviors.
- Overall comparable performance with vision-based methods.



Acknowledgements

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#26

GlucoCheck: Non-invasive AI-powered blood glucose monitoring device for older adults with diabetes

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Motivation

The US faces a metabolic disease epidemic in the older adults' population, with more than 47% of people over age 60 diagnosed with metabolic syndrome and more than 30% of adults over 65 diagnosed with diabetes. To manage these conditions, monitoring blood glucose concentration (BG) and taking appropriate action when values stray from safe levels is imperative.

Unfortunately, BG monitoring involves either a cumbersome process of drawing blood several times daily, implanting needles under the skin, or relying on non-invasive devices that are expensive, inconvenient and/or inaccurate. Frequent finger-prick blood draws, and other invasive methods increase the risk of infection or tissue damage, particularly in seniors with reduced skin elasticity and delayed immune response. Thus, *an accurate non-invasive device for BG monitoring* would present a life-changing option for millions of elderly patients.

Product and Objectives

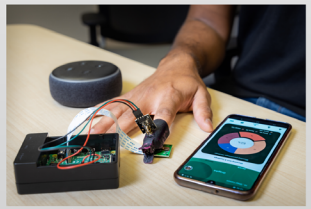

Fig 1. GlucoCheck original prototype.

We developed GLUCOCHECK, a non-invasive AI-powered blood glucose monitoring device for older adults with diabetes

The goals of this project are:

1. To improve the accuracy of GlucoCheck in older adults with *MatchALL algorithm*.
2. Test *Usability* of GlucoCheck by older adults.

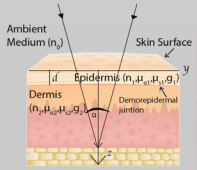

Fig 2. Skin light absorption

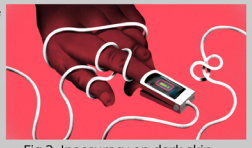

Fig 3. Inaccuracy on dark skin

Prototypes Development

We tested different types of wavelengths to determine the most accurate wavelength for any type of skin.

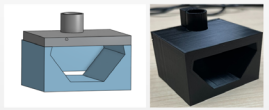

Fig 4. 2nd Prototype (Left) 3D design. (Right) prototype

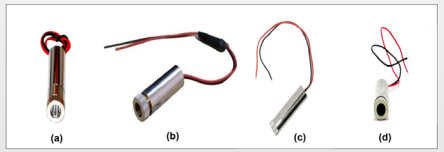

Fig 5. Tested wavelengths (a) 650nm (b) 808nm (c) 830nm (d) 850nm

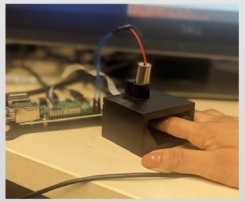

Fig 6. Second Prototype

Fig 7. Ring prototype

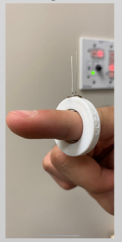

Fig 7. Ring

We followed the Maximum Permissible Exposure (MPE) that represents the minimum irradiance or radiant exposure that can affect skin without causing biological harm. The MPE values for all our lasers are well below $1.0\,mW/cm^2$ confirming their safety for use on the skin.

Wavelength (λ)	Power (mW)	C_A Factor	Exposure Time (s)	MPE (J/cm^2)	MPE (mW/cm^2)	MPE (W/cm^2)
0.650 (μm)	5	1	8	$(1.1)C_A(t^{0.25} = 1.85$	231mW/cm²	0.231W/cm²
0.808 (μm)	20	$(10)^{(0.002(808-.7)}$		$(1.1)C_A(8^{0.25} = 3.0$	375mW/cm²	0.375W/cm²
0.830 (μm)	20	$(10)^{(0.002(830-.7)}$		$(1.1)C_A(8^{0.25} = 3.4$	425mW/cm²	0.425W/cm²
0.850 (μm)	20	$(10)^{(0.002(850-.7)}$		$(1.1)C_A(8^{0.25} = 3.7$	426mW/cm²	0.426W/cm²

Fig. 8. MPE for each laser wavelength used in GlucoCheck

Fig 9. Mobile APP and GlucoCheck infrastructure

Methodology

Features Extraction: Each absorption image is converted into image tensors and individual arrays. Other image and pixel statistics are calculated in frequency and time domain

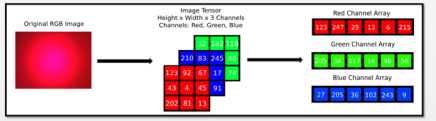

Fig. 10. Demonstration of features dataset creation

Model Selection: In our model, we combine AdaBoost and KNN as complementary strategies, employing AdaBoost for training the data and adding a weighted KNN algorithm on the classifiers produced by AdaBoost to generate accurate results.

	RM	GM	BM	GBM
Random Forest	12.85 - 87.23%	12.63 - 86.52%	13.91 - 85.82%	12.74 - 88.65%
Elastic Net	15.68 - 84.04%	16.89 - 85.11%	15.55 - 81.56%	14.41 - 83.69%
KNeighbors	9.55 - 90.78%	14.3 - 86.17%	15.81 - 84.4%	12.43 - 87.59%
Support Vector	14.3 - 87.94%	15.02 - 89.01%	14.58 - 87.23%	13.28 - 87.94%
Bayesian Ridge	15.52 - 84.04%	17.43 - 85.46%	15.52 - 82.62%	14.3 - 83.33%
XGBoost	13.03 - 86.88%	12.86 - 88.3%	13.6 - 86.52%	12.89 - 87.59%
AdaBoost	9.4 - 90.78%	12.74 - 86.88%	13.41 - 87.59%	13.18 - 86.52%

Fig. 11. Model Testing Results for each features datasets RM (Red Measurements), GM (Green Measurements), BM (Blue Measurements), GBM (Green Blue Measures) - Error MAE + Clark Error Grid

Data Collection

Fig. 12. Data Collection

IRB-FY23-249 - 11/39 older adults
Protocol:
Blood samples of the participants were taken using a flexible blood catheter always under supervision a certified phlebotomist. Images of fingers were taken with GlucoCheck glucose identification. Participants need to be in fasting mode and later were given an oral glucose tolerance test. Samples were performed at 10-, 20-, 30-, 60-, 90-, and 120 minutes. Skin color, temperature and mousier of finger were taken.

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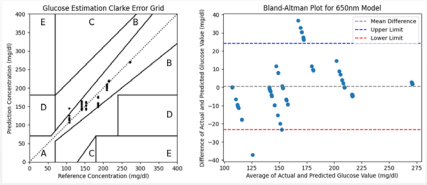
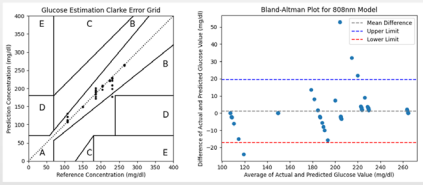
Publications & Media

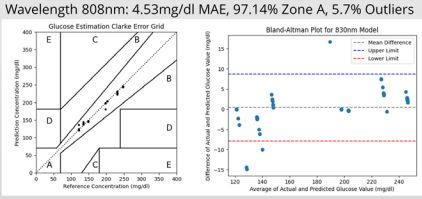
Results



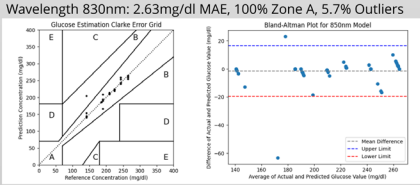
Wavelength 650nm: 7.82mg/dl MAE , 98.57% Zone A, 10% Outliers



Wavelength 808nm: 4.53mg/dl MAE, 97.14% Zone A, 5.7% Outliers



Wavelength 830nm: 2.63mg/dl MAE, 100% Zone A, 5.7% Outliers



Wavelength 850nm: 3.57mg/dl MAE, 98.57% Zone A, 2.9% Outliers

Conclusion

GlucoCheck compared with YSI 2300STAT has a statistical accuracy of ±2.63mg/dl with a wavelength of 830nm. It has a clinical accuracy >90% in in Zone A of the Clark Grid Error. GlucoCheck also minimizes the outliers and increase the agreement with a wavelength of 850nm.

Acknowledgements

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#27

Machine Learning to Predict Post-COVID-19 Cognitive Decline and Dementia

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Background and Objectives

Problem:
There is an urgent need to identify novel methods to evaluate the impact of COVID-19 on the dementia risk of older adults while facilitating access for those in low-resource settings.

- Cognitive deficits are frequently observed following COVID-19 illness, particularly in the domains of memory, executive functioning, processing speed and attention.
- COVID-19 may increase the risk for Alzheimer's disease or potentiate the onset of symptoms in at-risk older adults.
- The COVID-19 pandemic widened disparities in health outcomes.
  - Older adults and members of underrepresented minority groups were disproportionally affected.
- People living in underserved urban as well as rural communities face distinct challenges in accessing dementia care due to factors such as transportation limitations and scarcity of skilled providers.

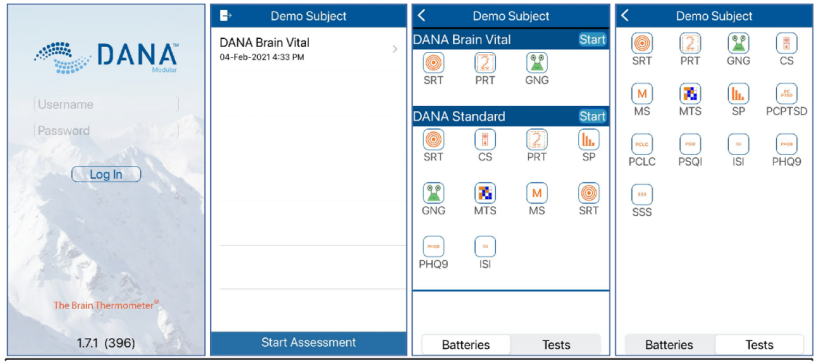
Objective:
This project seeks to develop a more accurate, reliable, and accessible method to detect and predict cognitive dysfunction and risk of Alzheimer's disease in older adults following COVID-19.

Approach:
- We will apply machine learning to:
  - the remote, longitudinal, app-based measurement of cognition
  - demographic characteristics
  - Features of the acute COVID-19 illness and related treatment

Pilot Project Highlights

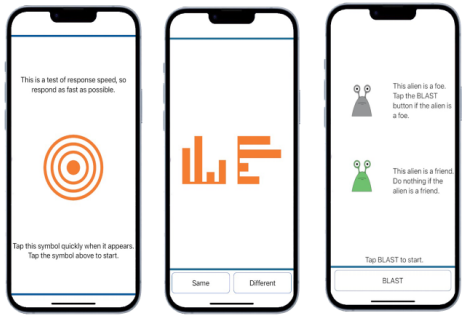
Study Design & Participants:
- This prospective cohort study assesses cognition remotely on 6 occasions over 3 months using a smart-device application
- Participants are ≥ 60 years old, have a documented history of COVID-19, and have an Internet-connected smartphone or tablet
- Recruitment sources: the Johns Hopkins Post-Acute COVID-19 Clinic and the Hopkins Opportunities for Participant Engagement Registry.

DANA™ mobile application:
- The FDA-cleared DANA™ mobile application was developed and validated to detect subtle cognitive impairment
- 7 cognitive tests: Measure simple and procedural reaction time, processing speed, visual working memory, spatial processing, response inhibition, and memory
- Symptom inventories: Measure depression (PHQ), anxiety (GAD), subjective cognitive dysfunction (ASRS)
  - Rich DANA™ data:
    - Accuracy, mean reaction time, and throughput
    - Trial-by-trial response data resulting in >200 data points per administration
    - Each data point is described by multiple parameters such as response time, inter-trial interval, and trial difficulty
    - Captures intra-individual and intra-task variability, which are risk factors for Alzheimer's disease, while also measuring fine-grained changes over repeat assessments
    - Provides a performance-based measure of cognitive fatigue



Project Status

Enrollment:
- Current enrollment: N = 20
  - Mean age: 66 years
  - Mean education: 14.9 years
  - Race: 25% non-white
  - Mean MoCA : 18/22 (normal ≥ 19/22)
  - Mean DANA adherence: 89.4% completion of assigned assessments
- Goal: n = 120
  - 20% of participants residing in rural areas
- Interim data analysis planned at n = 60



Future

We will expand the present study to employ longer follow up periods and dementia outcomes to further refine the algorithm, allowing for development of precision models of AD risk that exceed existing gold standard approaches and allow improved patient access.

Acknowledgements

National Institute on Aging Grant P30AG073104

#28

Detection of Falls and Other Health Events Using Sound, Activity monitoring and Machine Learning

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MassAITC AD/ADRD Focus Pilot Core

MassAITC
Massachusetts AI and Technology Center for Connected Care in Aging & Alzheimer's Disease

Background

Falls annually cause **32,000** deaths, **7 million** injuries and over **$50 billion** in Medicare costs. Our research presents a novel approach to detect falls using audio and activity monitoring. The research will also study if the system can reduce an older adult's fear of falling which may also decrease falls.

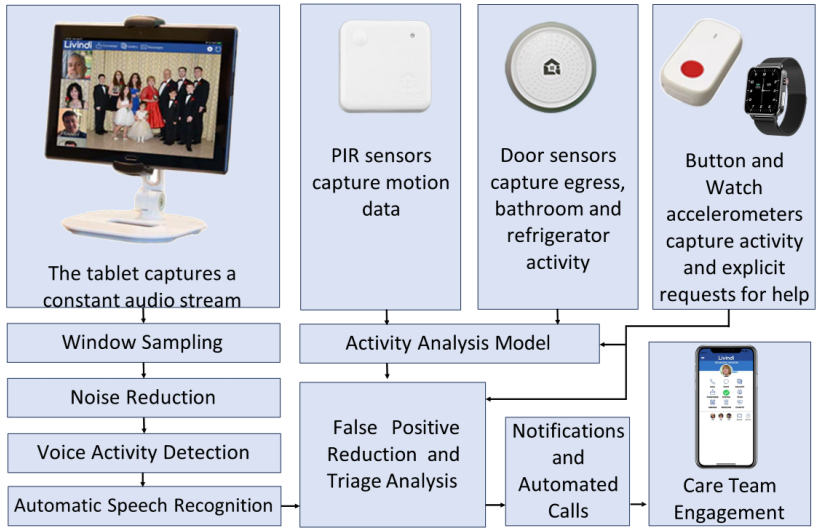
Livindi is used by thousands of older adults to stay healthy and safe using **communication**, **monitoring** and **Medicare-covered virtual clinical services**. The complete Livindi platform provides a tablet, call button, passive activity sensors, biometric sensors and enterprise tools.

Our research focuses on real-time detection of verbal requests for help as well as a model detecting changes in activity patterns to determine if someone has fallen. If a fall is detected, the system will engage the care team via an App on their phone.

Objectives

- Detect falls by listening for the phrase "**Help Me**", on-device, and monitoring for changes in activity patterns using sensors.
- Reduce fear of falling based on changes in the Falls Efficacy Scale (FES).
- Allow listening for alternative phrases without re-training the audio model.

Project Highlights



Methods Several methods were used for ASR including training an RNN model on audio samples saying "*Help Me*". This method was limiting and had a high error rate with background noise. We ultimately used a weak-supervision model with better noise reduction and dynamic triggering.

Milestones and Commercialization The solution is commercialized and launched in Q1 2024 on the Livindi platform. We are currently fine-tuning the models and the False Positive Reduction. The study will show how accurately it detects falls and calls for help and if it can reduce fear of falling which studies show may also reduce falls.

Participant Enrollment Recruitment begins Q2 2024. Participant criteria includes: age 65 or older, can move independently with or without walking devices, lives in a home with one egress door and may have cognitive impairment. Participants will be provided the Livindi system for the duration of the study and will have full use of its other features including video calling, picture sharing and caregiver support.

Conclusions

Our research addresses a critical healthcare issue by leveraging ASR and activity monitoring technology to detect falls, a leading cause of injury and high medical costs. By integrating audio detection of the phrase "Help Me" with an activity monitoring system, we have demonstrated a novel, proactive approach to enhance the safety and well-being of seniors.

In Q1 2024, we launched the technology on the Livindi platform. Once enrollees are in the study, we will also determine if the system can help reduce fear of falling by administering the Falls Efficacy Scale survey to enrollees before the study begins and after the study completes.

The research will also be used to provide proactive voice prompts used to confirm detection of other health issues based on sensor data for the in-home virtual care system.

Acknowledgements

MassAITC National Institute on Aging Grant P30AG073107

#29

A Digital Biometric Approach to Reducing Hospital Admissions for Underserved Older Adults with COPD

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Background

- Chronic obstructive pulmonary disease (COPD) poses significant mortality and morbidity in elderly population with disproportionate under-diagnosis and management of individuals with ethnic and socioeconomic disparities.
- Significant comorbidities, challenges with accessing care, and infrequent clinic visits are barriers to detecting and managing COPD.
- Home management of COPD patients is crucial to reduce morbidity and mortality, decrease hospitalizations and ER visits, and improve overall quality of life in the aging population.
- Conventionally used for early detection of COPD exacerbations, home spirometry faces significant limitations in the elderly due to adherence as well as physical & cognitive challenges.
- An innovative solution involves passive assessment of acoustic data from cell phone recordings, as a surrogate for spirometry, to detect COPD exacerbations unobtrusively.

Objectives

1. Develop a *COPD Care* mobile app and integrate the audio-based COPD metrics, educational material, and messaging protocols into it.
2. Complete usability testing of the *COPD Care* app prototype with older adults with COPD in a laboratory setting (2 rounds of testing with 5 subjects each).
3. Conduct a feasibility pilot of the working *COPD Care* mobile app over an 8-week period in the homes of 20 older adults with COPD.

Pilot Project Highlights

Data collection

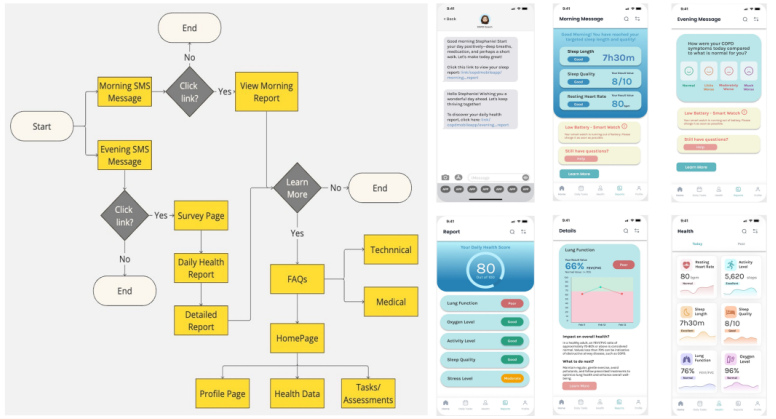
1. Demographics: Age 65, of minority or low socioeconomic status, speak English, have a smart cellphone, and with at-least moderate COPD.
2. Static variables: GOLD Stage, typical sleep time, typical walking time
3. Dynamic variables: Peak flow and FEV1 (from home spirometer), heart Rate, SpO2, activity steps, stress level, sleep length and quality (from smart watch).

Outcomes

1. *Primary outcomes*
   a) App satisfaction and ease-of-use: via single-item questionnaire (mean ± SD)
   b) Satisfaction with overall clinical care: within-subject t-test
1. *Secondary outcomes*
   a) Engagement: via monitored system usage (mean ± SD)
2. *Exploratory outcomes*

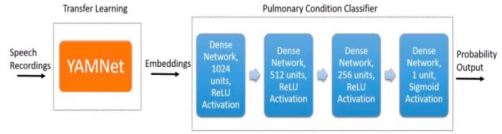
a) FEV1–within-subjects t-test.
b) Q of L— within-subjects t-test of CAT score (QR code for CAT score)
c) Voice-based Pulmonary Function (VPF)–correlate VPF to COPD symptoms, SpO2, and step counts.

COPD Care Mobile App Figma Prototype



Motivation & Innovation

- Monitor underserved older adults with COPD at home using an **unobtrusive** metric derived from **acoustic features** collected during regular cell phone use to detect preventable exacerbations that would, otherwise, lead to hospitalization.
- AI-based metric was developed by **Samsung Research America** using deep learning algorithms trained on large COPD data sets.
- Speech recordings are processed using **pre-trained YAMNet** to obtain embeddings, serving as input features for a COPD classifier based on fully connected networks.
- The final output of the sigmoid classification is a probability value, with **a value > 0.5 indicating the likelihood of the speech recording being from a pulmonary origin.**



Conclusions

If results support the outcome, data from this innovative pilot study could be used to inform a larger follow-on clinical trial with a larger sample of COPD patients towards commercialization and nation-wide use of *COPD care* App.

Acknowledgements

National Institute on Aging grant P30AG073107

#30

AI-based assessment of dementia etiologies

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BOSTON UNIVERSITY

BACKGROUND & OBJECTIVE

- Overlapping symptoms in various forms of dementia highlight the urgent need for better diagnostic methods.
- The scarcity of neurologists, especially in remote and developing regions, intensifies the need for more accessible screening tools.
- Recent regulatory approvals of disease-modifying therapies for Alzheimer's disease emphasize the importance of early risk detection.
- Reliance on in-depth clinical evaluations, cognitive testing, and MRI scans for diagnosis calls for specialist expertise, underscoring the demand for advanced, user-friendly diagnostic technologies in primary care and general neurology.
- Our objective was to develop an AI model that harnesses a broad array of data, including demographics, person-level and family medical history, medication use, neuropsychological assessments, functional evaluations, and multimodal neuroimaging, to identify the etiologies contributing to dementia in individuals.

METHODS

Fig 1. Data modalities and study population.

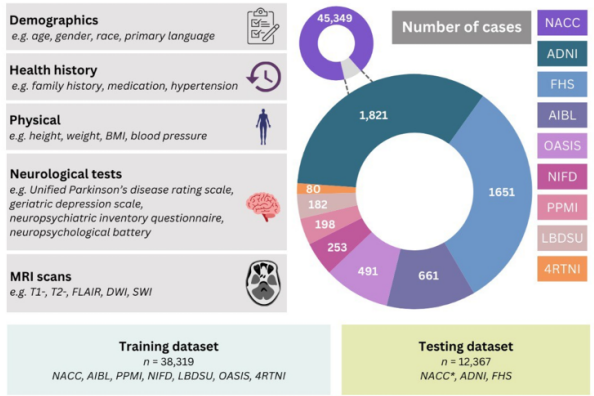

Figure 1. Our model for differential dementia diagnosis was developed using diverse data modalities, including individual-level demographics, health history, neurological testing, physical/neurological exams, and multi-sequence MRI scans. These data sources were aggregated from nine independent cohorts: the National Alzheimer's Coordinating Center (NACC), Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, the frontotemporal lobar degeneration neuroimaging initiative (NIFD), the Parkinson's Progression Marker Initiative (PPMI), the Australian Imaging, Biomarker and Lifestyle Flagship Study of Ageing (AIBL), the Open Access Series of Imaging Studies, the 4 Repeat Tauopathy Neuroimaging Initiative (4RTNI), and the Lewy Body Dementia Center for Excellence at Stanford University (LBDSU), and the Framingham Heart Study (FHS).

Fig 2. Multimodal machine learning architecture.

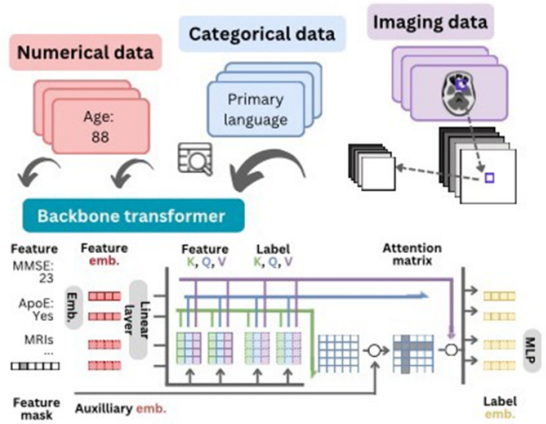

Figure 2. Each input feature (numerical, categorical or imaging data) was processed into a fixed-length vector using a modality-specific embedding strategy and fed into the transformer as input, where the transformer served as the scaffold for the modeling framework. A linear layer was used to connect the transformer with the output prediction layer.

RESULTS

Fig 3. Performance of the model on individuals along the cognitive spectrum.

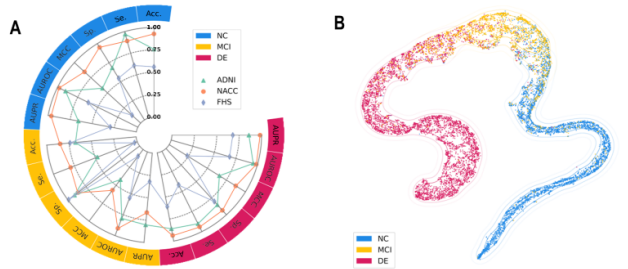

Figure 3. **(A)** Radar plot illustrating the performance of the model on individuals with normal cognition (NC), mild cognitive impairment (MCI), and dementia (DE) is shown. We present a range of metrics including mean values along with their standard deviations, for model accuracy, sensitivity, specificity, precision, area under the receiver operating characteristic curve, area under the precision-recall curve, F1-score, and Matthews correlation coefficient. **(B)** Two-dimensional t-distributed stochastic neighbor embeddings obtained from the penultimate layer of the model are shown. The legend in the lower-left corner indicates the color-coding representing NC, MCI and DE, respectively.

Fig 4. Model alignment with clinical dementia ratings.

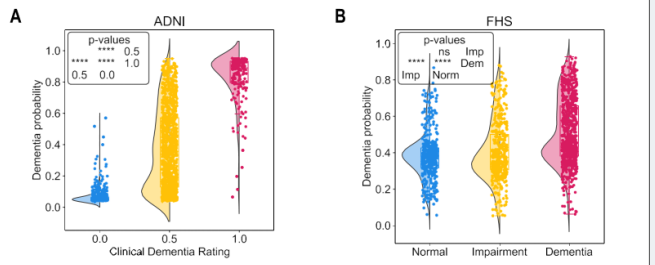

Figure 4. Raincloud plots with overlying violin and box diagrams are shown to denote the distribution of clinical dementia rating scores (horizontal axis) versus model-predicted probability of dementia (vertical axis), on the ADNI and FHS cohorts, respectively. Significance levels are denoted as 'ns' (not significant) for $p \geq 0.05$; * for $p < 0.05$; ** for $p < 0.01$; *** for $p < 0.001$; and **** for $p < 0.0001$ based on Kruskal-Wallis H-test for independent samples followed by post-hoc Dunn's testing with Bonferroni correction.

Fig 5. Head-to-head comparison with neurologists.

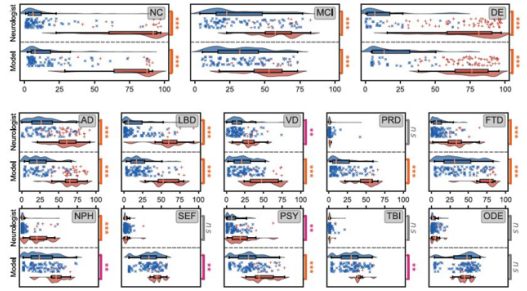

Figure 5. Comparison between model-predicted probability scores and the assessments provided by practicing neurologists is shown. For the analysis, neurologists were given 100 randomly selected cases encompassing individual-level demographics, health history, neurological tests, physical as well as neurological examinations, and multi-sequence MRI scans. The neurologists were then tasked with assigning confidence scores for NC, MCI, DE, and various dementia etiologies. The boxplot in blue indicates the distribution of confidence scores for true negative cases, while the boxplot in red signifies true positive cases. The symbol '+' represents true positive cases, and 'x' denotes true negative cases. Significance levels are denoted as: ns (not significant) for $p \geq 0.05$; * for $p < 0.05$; ** for $p < 0.01$; *** for $p < 0.001$; and **** for $p < 0.0001$. These levels were determined using pairwise comparisons via the Brunner-Munzel test.

CONCLUSIONS

- Our algorithmic framework introduces fresh possibilities for dementia screening across various clinical settings and drug trials, with substantial implications for optimizing patient management.

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#31

A speech-processing algorithm for automatic screening of Black patients with mild cognitive impairment and early dementia in home healthcare setting

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Background

Mild cognitive impairment (MCI) and early-stage dementia (ED) are rising public health concerns, affecting one in five older adults over 60. Despite nationwide efforts, more than 50% of MCI-ED patients remain undiagnosed. Data from the National Institute on Aging (NIA) reveals that Black older adults face a twofold higher risk of cognitive impairment compared to their White counterparts,3 yet are less often diagnosed Current screening algorithms, based on electronic health records (EHR), have suboptimal performance in early detection of MCI-ED. We hypothesize that integrating audio-recorded home health patient-nurse verbal communication with EHR data can enhance screening algorithms, enabling timely identification of patients with cognitive impairment, particularly among Black patients.

Objectives

This study aimed to develop artificial intelligence-based pipeline for audio-recording home healthcare patient-nurse verbal communication, modeling the audio-recorded data (using natural language processing methods), and developing machine learning models for timely identification of patients with mild cognitive impairment.

Method

The development of this pipeline consists of four components. Component-1: We created a novel procedure for audio-recording patient-nurse verbal communication in a home healthcare setting. As part of this procedure, we tested the usability of seven audio-recording devices in both laboratory and HHC settings. Also, we interviewed five nurses and ten patients to understand the facilitators and barriers of integrating audio-recording encounters with the home healthcare workflow (Figure 1). Component-2: We measured the accuracy of three common commercial and open-access automatic speech recognition (ASR) systems to select an ASR system with high accuracy for automatic transcription of audio-recorded verbal communications. Component-3: We developed machine learning classifiers for automatically differentiating the patient's speech from the nurse's speech in the audio-recorded patient-nurse verbal communication. To develop this classifier, several machine learning algorithms were trained and evaluated on natural language processing features (e.g., lexical richness, n-grams) generated from patients' and nurses' utterances. Component-4: We developed a screening algorithm by training and evaluating several ML models on the combination of audio-recorded patient-nurse verbal communication, home healthcare clinical notes, and a set of clinical variables from EHR system, such as the list of medication and diagnoses for 28 Black patients. Natural language processing features and patterns of communications were extracted from the transcribed verbal communications. Clinical notes were processed using advanced natural language processing methods such as Clinical BERT (Figure 2).

Results

Component-1: According to nurses' evaluations, Saramonic Blink, a portable wearable audio-recording device, received the highest score for usability. Both nurses and patients found the audio-recording procedure satisfactory. Component-2: We selected Amazon Web Services' General Transcribe for the automatic transcription of verbal communications due to the highest accuracy of its transcription (Word Error Rate = 0.26). Component-3: The performance of the classifier for differentiating patient speech from nurse speech had an F-score of 99%. Component-4: The initial performance of the screening algorithms for cognitive impairment detection using only patient-nurse verbal communication had an F-score of 81%, outperforming advanced algorithms analyzing EHR data (including clinical notes) by 10%. However, when EHR data and clinical notes were added to the patient-nurse verbal communication, the F-score increased to 83%. This suggests that patient verbal communication provides more insights for the early detection of cognitive impairment than EHR data.

Figure 1. Feasibility of Audio-recording Patient-Nurse Verbal Communication in Home Healthcare Setting

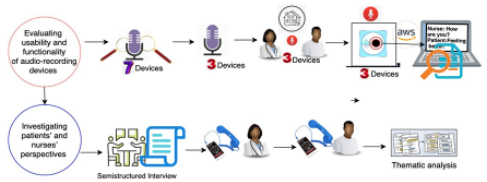
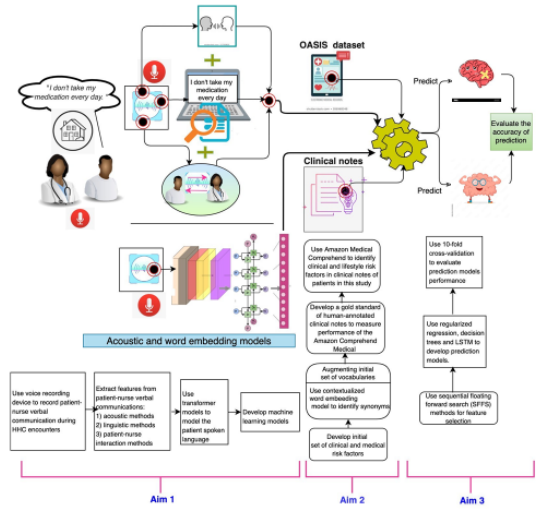


Figure 2. Overview of the Study Methodology



Conclusion

The MCI-ED screening algorithm developed using this pipeline for Black patients has strong potential to be integrated with home healthcare workflows to raise the attention of home healthcare teams to Black patients' cognitive status. Therefore, the home healthcare team can approach patients with appropriate interventions to mitigate risks.

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