Biometric Monitoring Device Workshop

CAMD CRITICAL PATH INSTITUTE

May 9-10, 2017

Advancing CDISC Standards for Biosensors Assessments in Clinical Drug Trials

Bethesda North Marriott Hotel and Conference Center

Bethesda, MD

The Potential of BMDs in Assessing Real-World Function

Jeffrey Kaye

Layton Professor of Neurology & Biomedical Engineering

ORCATECH - Oregon Center for Aging & Technology

NIA - Layton Aging & Alzheimer's Disease Center

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High Interest in Digital Technologies

IoT

CART --
Collaborative Aging (in P

- Interagency initiative w
  - NIA, NIBIB, NCI, N

Biometric Monitoring Device Workshop

$1M HOMESHARE GRANT AWARDED BY NSF

BY KAY CONNELLY | OCTOBER 18, 2016 | UNCATEGORIZED

August 2016 – The HomeSHARE initiative is a geographically distributed testbed to design, develop, and evaluate pervasive home-based technologies for aging-in-place. IU is the lead institution, with partners at University of Colorado, University of Virginia, Clemson University and University of Washington.

BOOKMARK THE PERMALINK.

NIH National Institute on Aging
Turning Discovery Into Health

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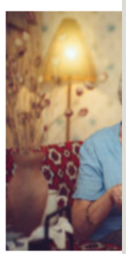
NEWSROOM

NIH initiative tests in-home technology to he age in place

January 25, 2017

Many older adults want to live at home independently as they age. Sometime from their family and friends—and the right technology. A new initiative led b Health (NIH) aims to help seniors age in place by developing a research platf related in-home sensors and other technologies.



CART—Collaborative Aging (in Place) Research Using Technology—unites NIH, academic, and industry experts to develop and test unobtrusive tools that record and track real-time changes in older adults' health status and activities. Launched in October 2016, the $7 million, 4-year project will take place in more than 200 homes in rural and urban communities across the United States.

"This project will provide a systematic way of investigating technology that may enable older people to remain independent and avoid hospitalizations and transitions into care facilities," said Nina Silverberg, Ph.D., of the National Institute on Aging project.

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ACD Precision Medicine Initiative Working Group Public Workshop

Mobile and Personal Technologies in Precision Medicine Workshop

On July 27–28, 2015, the Precision Medicine Initiative (PMI) Working Group of the Advisory Committee to the NIH Director (ACD) hosted a public workshop on the scientific, methodological and practical considerations to inform the incorporation of mobile and personal technologies in the national research cohort of one million or more volunteers. The workshop will be was held at the Intel Corporation campus in Santa Clara, California, and was videocast.

This workshop built on the unique scientific questions developed during the April 28–29 workshop, digital health data perspectives shared during the May 28–29 workshop, and

Email Updates

Sign up to receive email updates about the Precision Medicine Initiative.

Sign up for updates

Related Links

- PMI Working Group Final Report pdf
- NEJM Perspective: A New Initiative on Precision Medicine
- Precision Medicine Initiative and Cancer Research
- Precision Medicine Initiative

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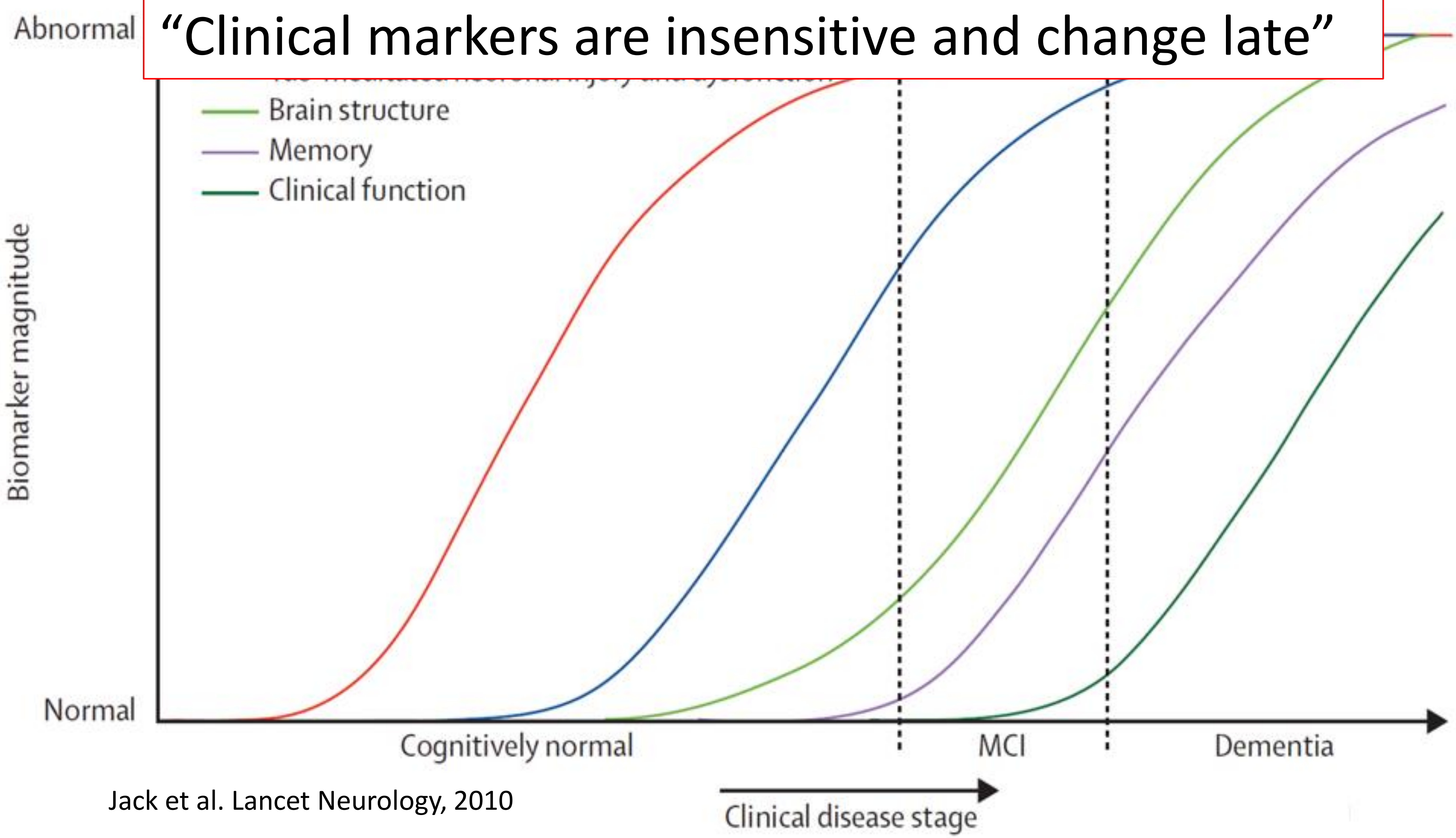
Why Biomarkers?

Progression of biomarkers in AD Progression

“Clinical markers are insensitive and change late”



Jack et al. Lancet Neurology, 2010

Change in IADLs are a Part of MCI…

Acta Neurol Scand 2003: 107 (Suppl. 179): 42–46

ACTA NEUROLOGICA
SCANDINAVICA
ISSN 0065-1427

Instrumental activities of daily living: a stepping-stone towards [...] diagnosis in subjects wit[...] impairment?

Nygård L. Instrumental activities of daily living: a stepping-st[...]
Alzheimer's disease diagnosis in mild cognitive impairment [...]
Acta Neurol Scand 2003: 107 (Suppl. 179): 42–46.
© Blackwell Munksgaard 2003.

This paper challenges the requirements of normal activitie[...]
living/instrumental activities of daily living (ADL/IADL) [...]

Mild Cognitive Impairment and Everyday Function: Evidence of Reduced Speed in Performing Instrumental Activities of Daily Living

Virginia G. Wadley, Ph.D., Ozioma Okonkwo, M.A., Michael Crowe, Ph.D., Lesley A. Ross-Meadows, Ph.D.

Jekel *et al. Alzheimer's Research & Therapy* (2015) 7:17
DOI 10.1186/s13195-015-0099-0

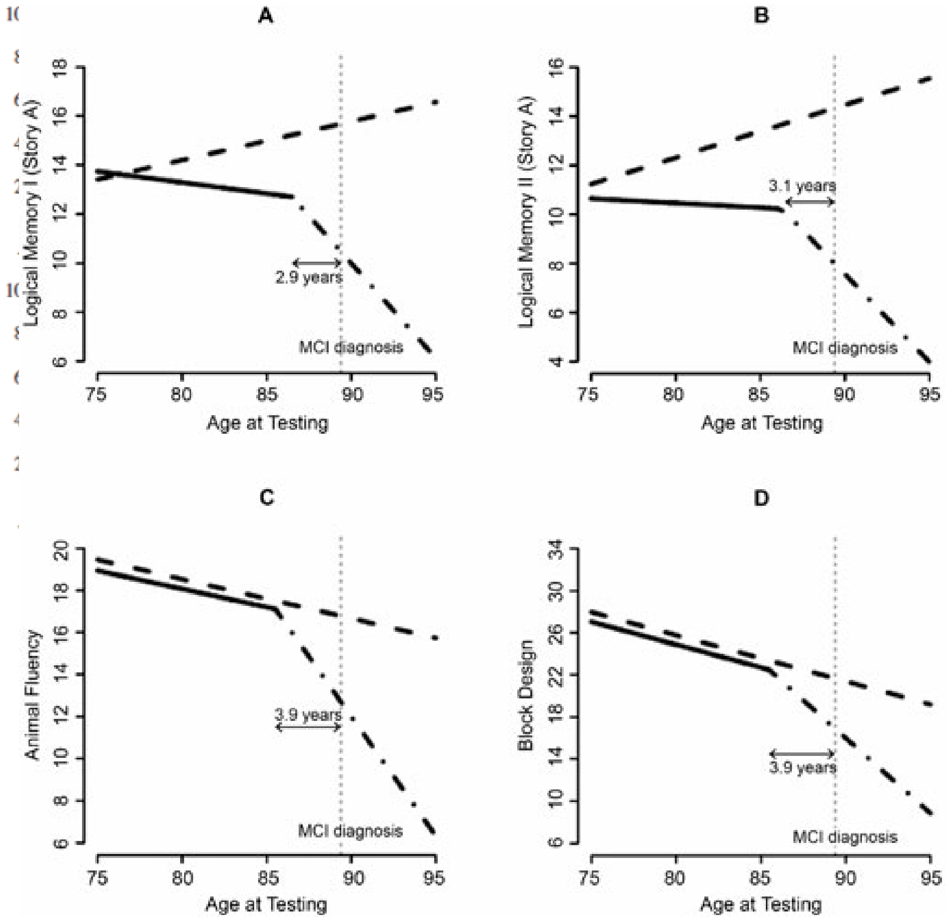
alzheimer's research&therapy

RESEARCH **Open Access**

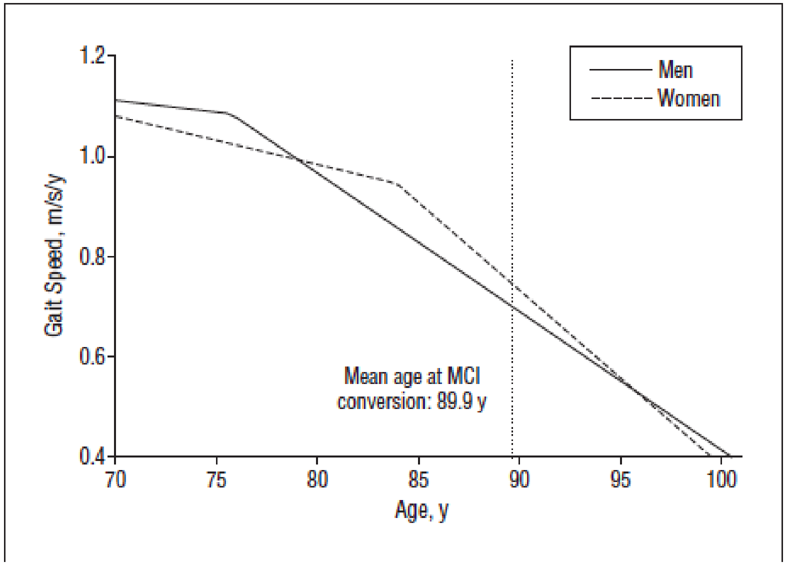
Mild cognitive impairment and deficits in instrumental activities of daily living: a systematic review

Katrin Jekel[1,2*], Marinella Damian[2], Carina Wattmo[3], Lucrezia Hausner[2], Roger Bullock[4], Peter J Connelly[5], Bruno Dubois[6], Maria Eriksdotter[7], Michael Ewers[8], Elmar Graessel[9], Milica G Kramberger[10], Emma Law[11], Patrizia Mecocci[12], José L Molinuevo[13], Louise Nygård[14], Marcel GM Olde-Rikkert[15], Jean-Marc Orgogozo[16], Florence Pasquier[17], Karine Peres[18,19], Eric Salmon[20], Sietske AM Sikkes[21], Tomasz Sobow[22], René Spiegel[23],

IADL Changes…*Precede* Dementia or MCI Dx by 7-10 Years

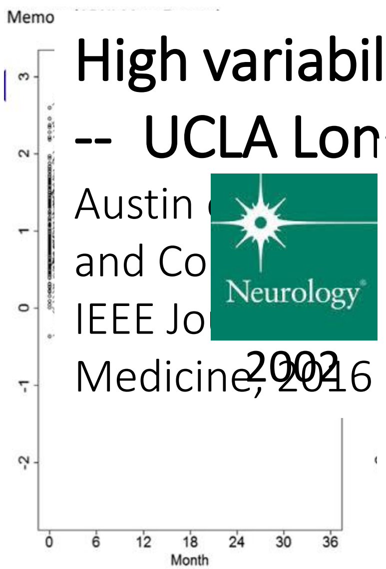


Howieson et al. Trajectory of mild cognitive impairment onset, JINS, 2008



Buracchio et al. The Trajectory of Gait Speed Preceding Mild Cognitive Impairment, Archives Neurol. 2010

Identifying Functional and Cognitive Change is Challenging using Episodic Testing and Self-Report

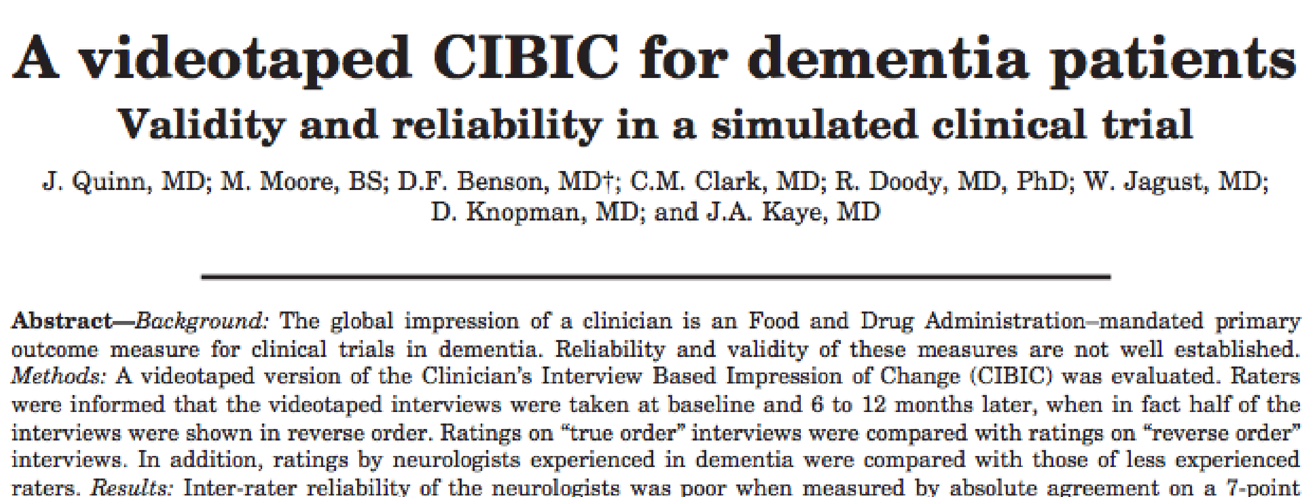


High variability in self-report measures

-- UCLA Lon...

Austin ...
and Co...
IEEE Jo...
Medicine, 2016

2002

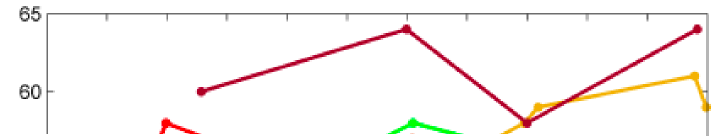


A videotaped CIBIC for dementia patients

Validity and reliability in a simulated clinical trial

J. Quinn, MD; M. Moore, BS; D.F. Benson, MD†; C.M. Clark, MD; R. Doody, MD, PhD; W. Jagust, MD; D. Knopman, MD; and J.A. Kaye, MD

Abstract—*Background:* The global impression of a clinician is an Food and Drug Administration–mandated primary outcome measure for clinical trials in dementia. Reliability and validity of these measures are not well established. *Methods:* A videotaped version of the Clinician's Interview Based Impression of Change (CIBIC) was evaluated. Raters were informed that the videotaped interviews were taken at baseline and 6 to 12 months later, when in fact half of the interviews were shown in reverse order. Ratings on "true order" interviews were compared with ratings on "reverse order" interviews. In addition, ratings by neurologists experienced in dementia were compared with those of less experienced raters. *Results:* Inter-rater reliability of the neurologists was poor when measured by absolute agreement on a 7-point



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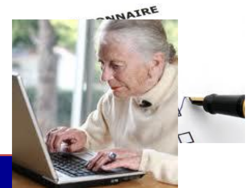
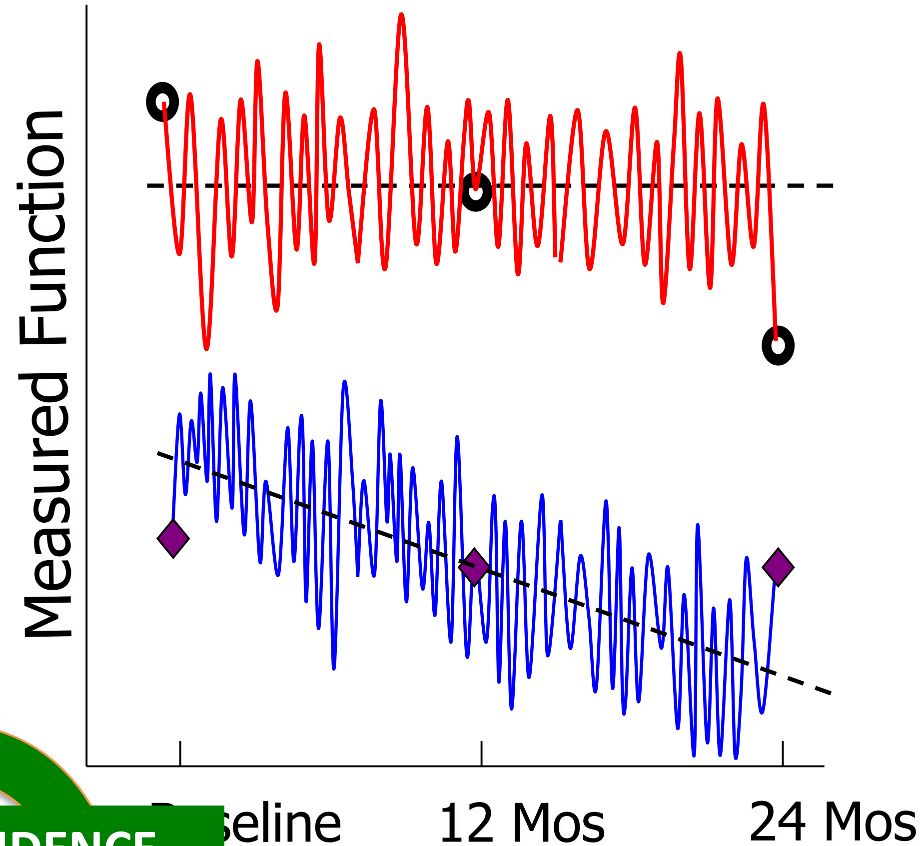
Which has brought us to BDMs in Trials…



- **Real-time**
- **Continuous**
- **Home-based**
- **Objective**
- **Unobtrusive**
- **Ambient**

- Pervasive Computing
- Wireless Technologies
- “Big Data” Analytics



EVIDENCE

?

Evidence for Use of BMDs in (Dementia) Trials

Journal of **Healthcare Engineering** · Vol. 6 · No. 1 · 2015 Page 71-84 71

1995-2014: 14 RCT's using ICT Devices in Dementia

Review of Information and Communication Technology Devices for Monitoring Functional and Cognitive Decline in Alzheimer's Disease Clinical Trials

Jagan A. Pillai MBBS, PhD* and Aaron Bonner-Jackson, PhD
Departments of Neurology and Lou Ruvo Center for Brain Health
Cleveland Clinic, Cleveland, OH, USA

Published in final edited form as:
JAMA Neurol. 2015 May ; 72(5): 582–588. doi:10.1001/jamaneurol.2014.4524.

Novel Methods and Technologies for 21st-Century Clinical Trials:

A Review

E. Ray Dorsey, MD, MBA
Department of Neurology, University of Rochester Medical Center, Rochester, New York
Center for Human Experimental Therapeutics, University of Rochester Medical Center, Rochester, New York

Search terms (1995-2014): *Alzheimer's disease, dementia, MCI, predementia, information and communication technologies, actigraphy, assistive technologies, monitoring devices, ICT devices, infra-red tracking, smart environments, Clinical trials.*

Search terms (2000-2014): *disease modeling* and *clinical trials*; *adaptive design*, *clinical trials*, and *neurology*; *Internet*, *clinical trials*, and *neurology*; and *telemedicine*, *clinical trials*, and *neurology* - 22/7976 articles were determined relevant and included in the review.

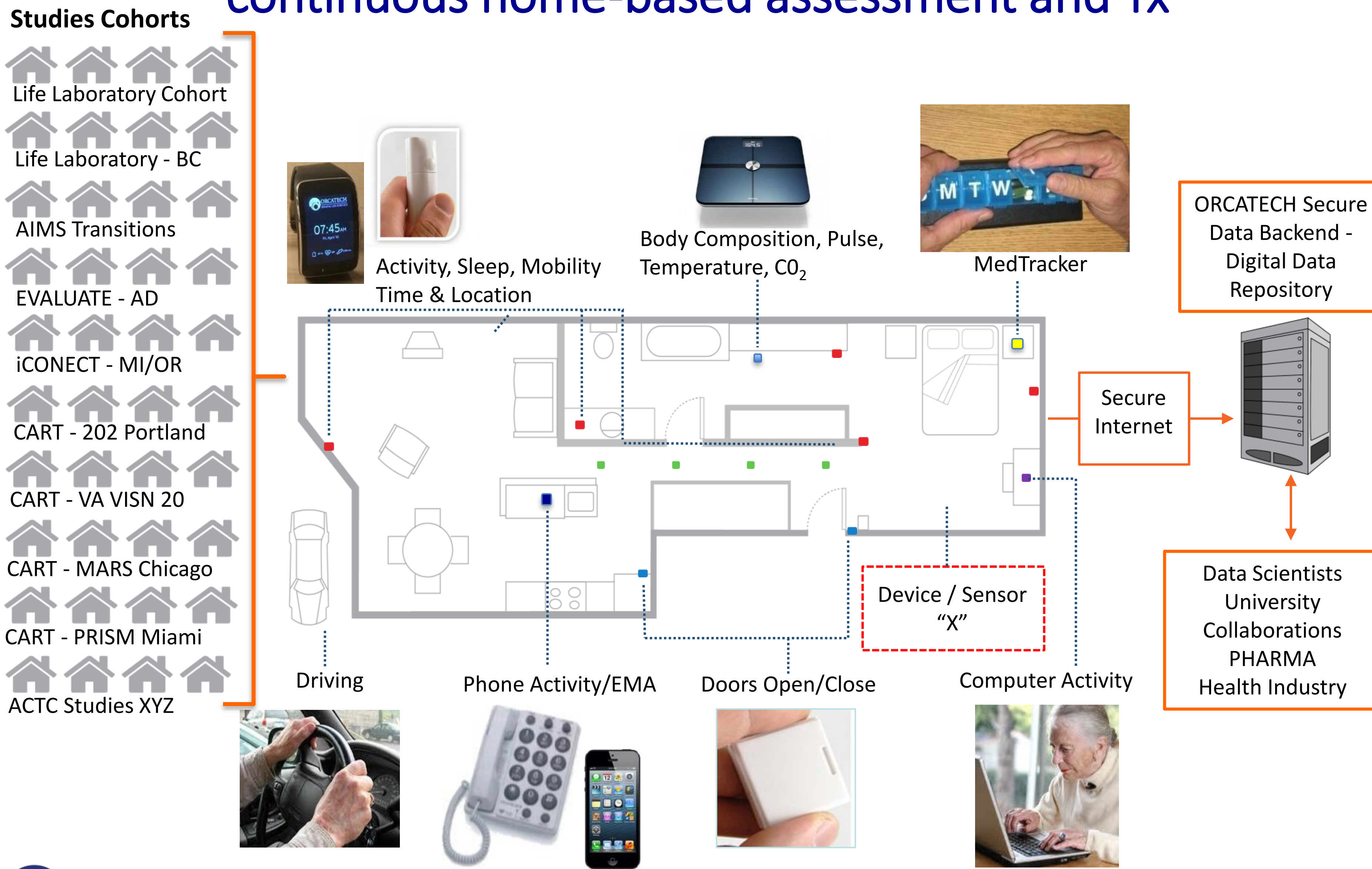
Table 2. Key Trends by Noninvasive Digital Technology (Number of Studies)

	SMARTPHONES/ PDAS	WEARABLE DEVICES	BIOSENSOR DEVICES	COMPUTERIZED SYSTEM	MULTIPLE COMPONENTS
Number of studies, *N* = 62, *n* (%)	12 (19)	11 (18)	7 (11)	6 (10)	26 (42)
Country, *n* (%)					
Non-U.S.[a]	6 (50)	7 (64)	5 (71)	2 (33)	16 (62)
U.S.	6 (50)	4 (36)	2 (29)	4 (67)	10 (38)
Disease category, *n* (%)					
Cancer	1 (8)	–	–	–	–
Cardiovascular	–	3 (27)	3 (43)	–	5 (19)
Metabolic disorders	2 (17)	1 (9)	1 (14)	–	6 (23)
Neurological	1 (8)	4 (36)	–	–	–
Psychological	2 (17)	1 (9)	–	1 (17)	–
Respiratory	2 (17)	–	2 (29)	1 (17)	9 (35)
Sleep disorders	–	2 (18)	–	–	1 (4)
Substance abuse	–	–	–	–	1 (4)
Weight management	4 (33)	–	–	4 (67)	3 (12)
Other/Multiple[b]	–	–	1 (14)	–	1 (4)
Age category, *n* (%)					
<20 years old	1 (8)	1 (9)	–	–	1 (4)
21–39 years old	1 (8)	2 (18)	–	–	–
40–64 years old	3 (25)	2 (18)	2 (29)	1 (17)	3 (12)
≥65 years old	1 (8)	1 (9)	–	–	4 (15)
>20 years old[c]	6 (50)	4 (36)	5 (71)	5 (83)	18 (69)
Not reported		1 (9)			

Considerations for BMD Development

- Ecological Validity (Users and Use Cases)
  - Data for discovery, drug development, registration?
  - How closely does the data reflect the ‘call of the wild’?
  - Is the methodology user friendly including trials teams friendly?
- Encoding (Data)
  - How does the data fare across the arc from initial generation to data lock (and beyond)?
  - Data standards/structures, provenance (capture, processing, recording, analytics, storage...)?
- Evidence Creation (Validation, Meaningfulness, Adoption)
  - What is needed to ensure that BMD data generated is valid, reliable and provides the intended meaning for trial outcomes?
  - Fit for regulators, payers, people?

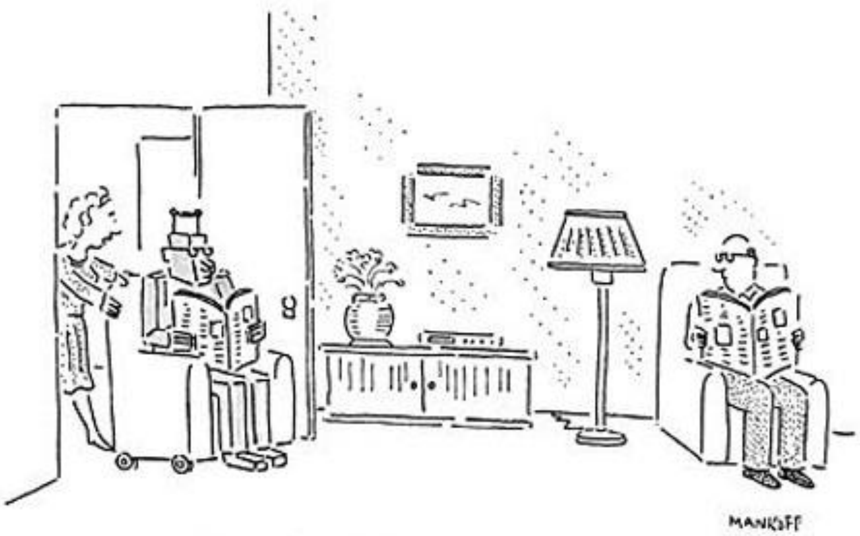
Technology ‘agnostic’ pervasive computing platform for continuous home-based assessment and Tx



Kaye et al. Journals of Gerontology, 2011; Lyons et al. Frontiers in Aging Neuroscience, 2015

Considering Use Examples

Emphasizing Motor Function, Sleep, and Cognition



"Don't panic. It's only a prototype."

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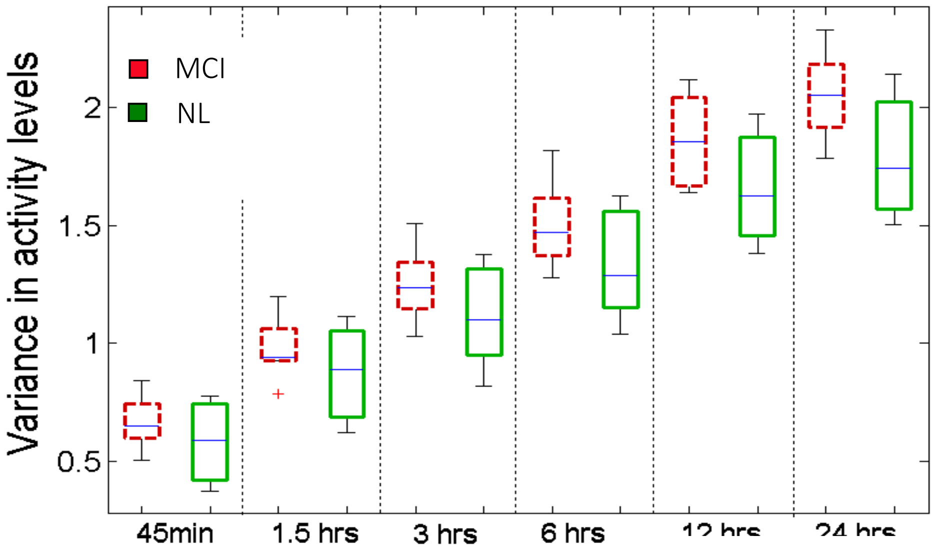
Physical Activity and Mobility Behaviors

Differentiation of early MCI

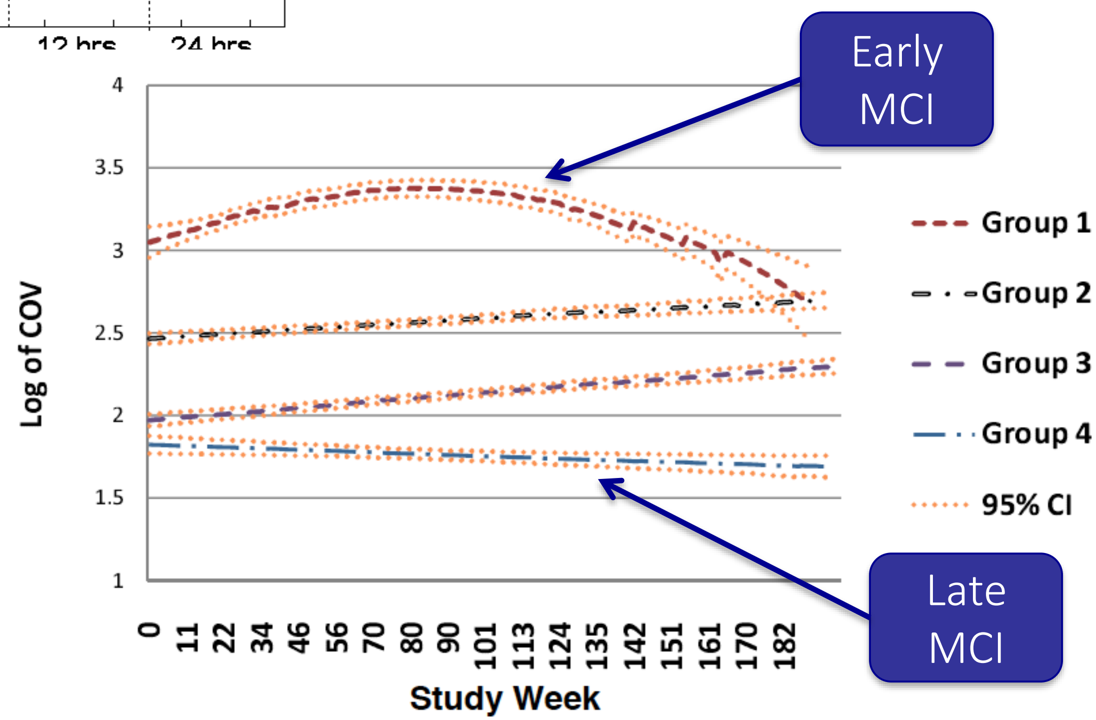


Activity patterns associated with MCI

Hayes et al. Alzheimers Dement, 2008

Trajectories of gait speed over time

Dodge, et al. Neurology, 2012



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Physical Activity and Mobility Behaviors

Room activity distributions differentiating MCI vs not MCI (n=85)

Room	Bedroom	Bathroom	Kitchen	Living Room	Combined
$F_{0.5}$ Score*	0.842	0.829	0.813	0.826	0.856

*$F_{0.5}$ Scores window size ω = 20 weeks; slide size = 4 weeks (with leave-one-subject-out cross validation)

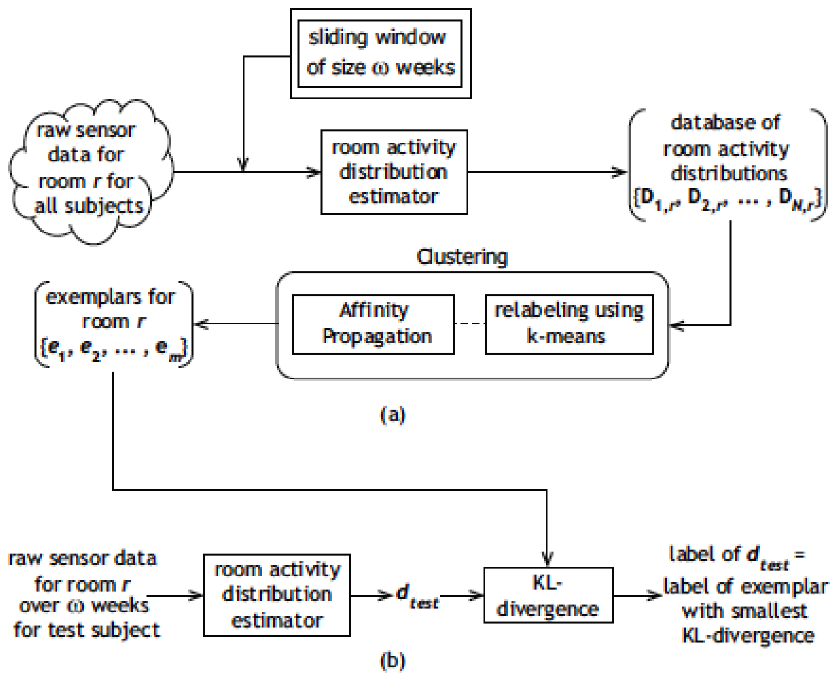
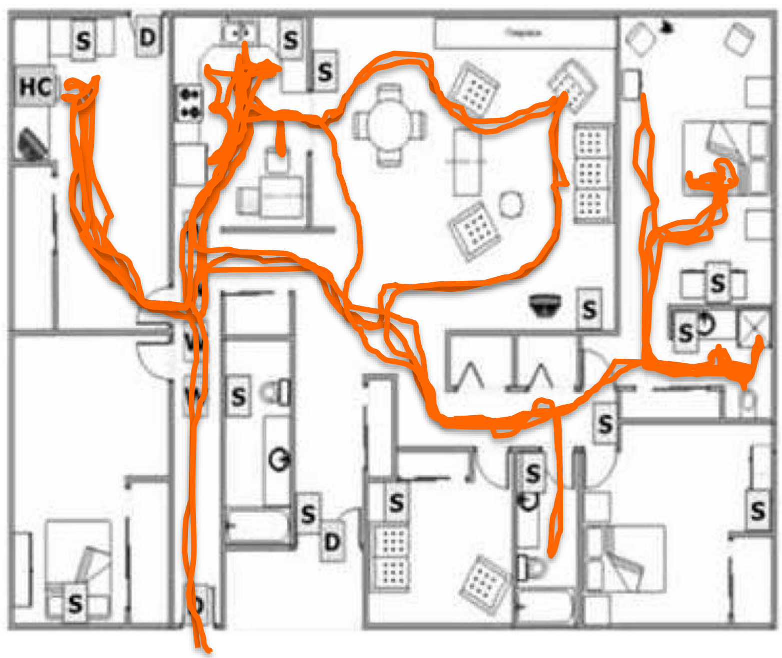


Fig. 2. General overview of the cognitive status recognition process using distributions corresponding to room r. (a) Training Stage. (b) Test Stage.



Akl et al. Journal of Ambient Intelligence and Smart Environments, 2015

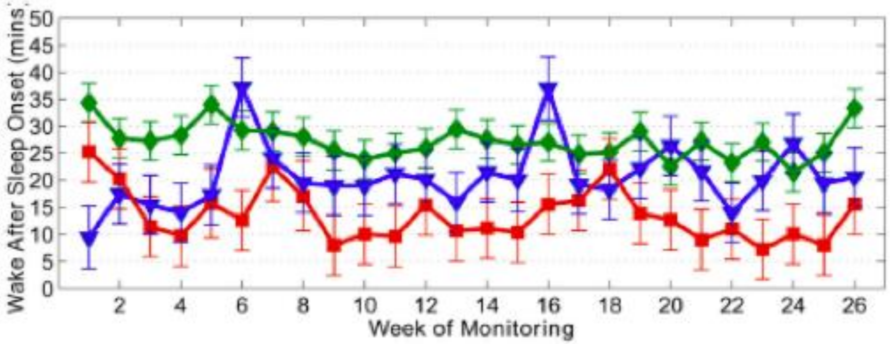
Night-time Behavior & Sleep

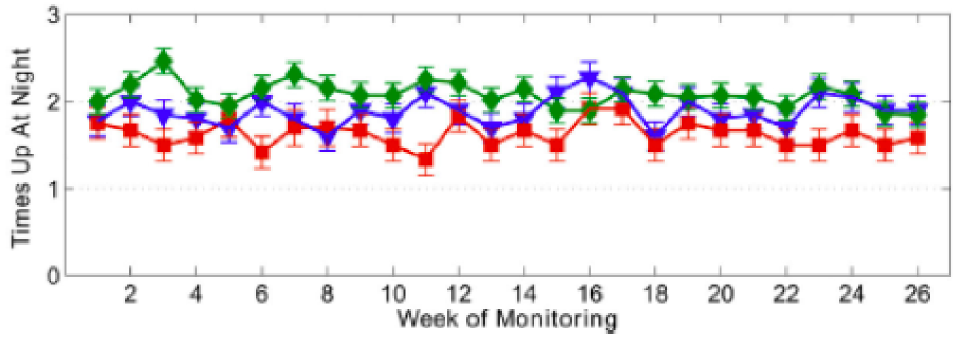
Differentiation of MCI

Normal -

NA-MCI -

A-MCI -





Objective Measure	Intact	aMCI	naMCI	P value
Movement in Bed (sensor firings)	9.4 ± 0.4	7.8 ± 0.9	10.9 ± 0.7	p < 0.05 (aMCI < naMCI)
Wake After Sleep Onset (mins)	27.2 ± 1.2	13.5 ± 2.6	20.6 ± 2.0	p < 0.001 (aMCI < intact, naMCI)
Settling Time (mins)	2.5 ± 0.07	2.3 ± 0.15	3.1 ± 0.11	p < 0.001 (naMCI > intact, aMCI)
Times up at night (# times)	2.1 ± 0.04	1.6 ± 0.10	1.9 ± 0.08	p < 0.001 (aMCI < intact, naMCI)
Total Sleep Time (hrs)	8.3 ± 0.04	8.5 ± 0.09	8.5 ± 0.07	NS

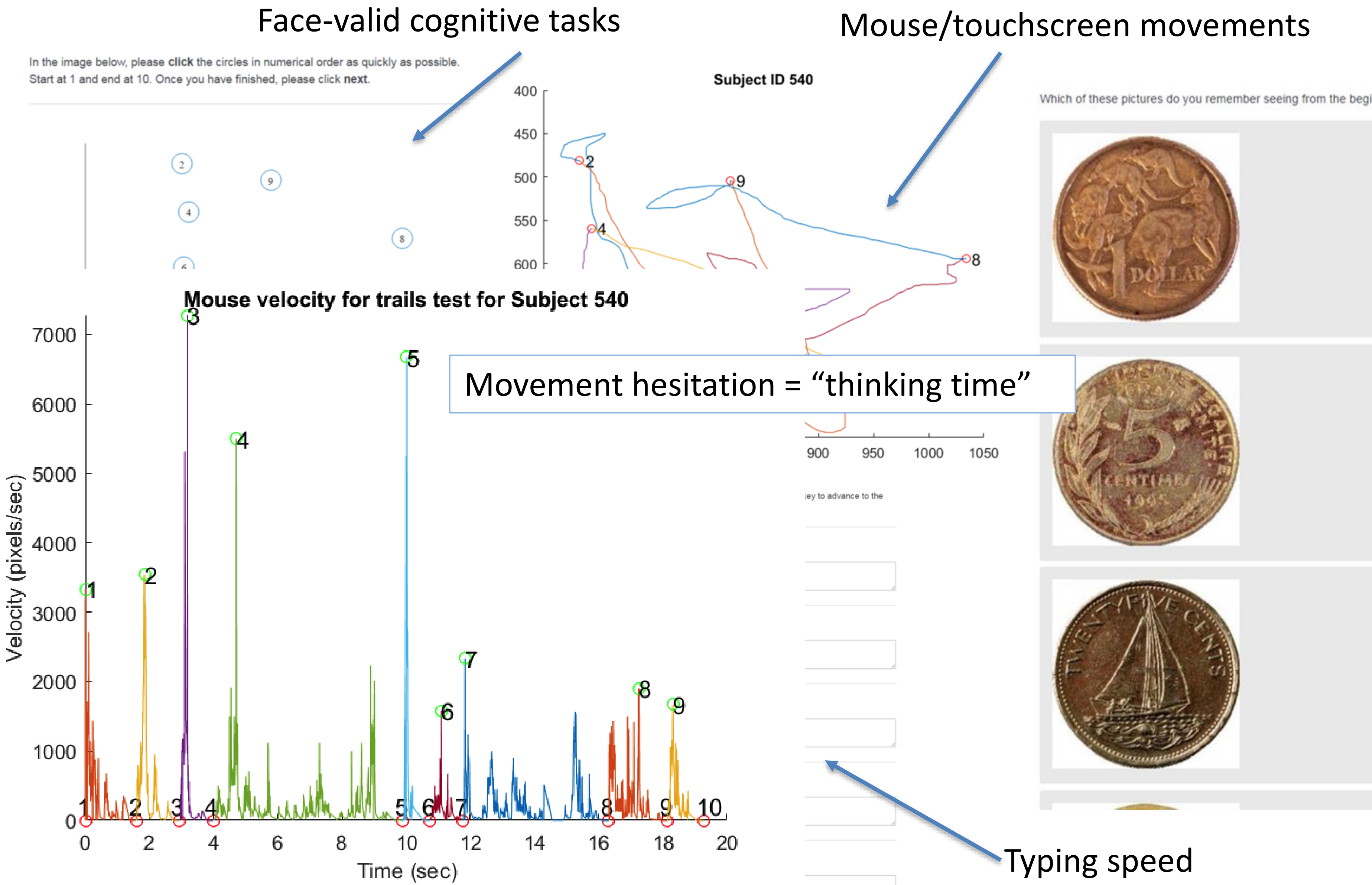
No Differences Between Groups in Self-Report Measures

Self-Report Measure	Intact	aMCI	naMCI	P value
Subjective Daytime Sleepiness	1.8 ± 0.2	1.5 ± 0.3	2.0 ± 0.3	0.69
Subjective Insomnia	1.3 ± 0.2	0.8 ± 0.3	1.6 ± 0.3	0.21
Subjective Restlessness	1.0 ± 0.1	0.4 ± 0.3	0.7 ± 0.2	0.34
Times up at night	1.1 ± 0.1	1.0 ± 0.3	1.0 ± 0.2	0.77

Hayes, et al. Alzheimer Dis Assoc Disord. 2014
Hayes, et al. IEEE Eng Med Biol Soc, 2010

Cognition: Computer/Internet-based Online Testing

Survey for Memory, Attention, and Response Time (SMART)



Cognitive Function Affected by Sleep History

Clin Neuropsychol. Author manuscript; available in PMC 2016 Feb 2.
Published in final edited form as:
Clin Neuropsychol. 2015 Jan; 29(1): 53–66.
Published online 2015 Feb 2. doi: 10.1080/13854046.2015.1005139

PMCID: PMC4346222
NIHMSID: NIHMS653075

The impact of sleep on neuropsychological performance in cognitively intact older adults using a novel in-home sensor based sleep assessment approach

Adriana Seelye,[1,2] Nora Mattek,[1,2] Diane Howieson,[1] Thomas Riley,[2,3] Katherine Wild,[1,2] and Jeffrey Kaye[1,2,3]

Author information ▶ Copyright and License information ▶

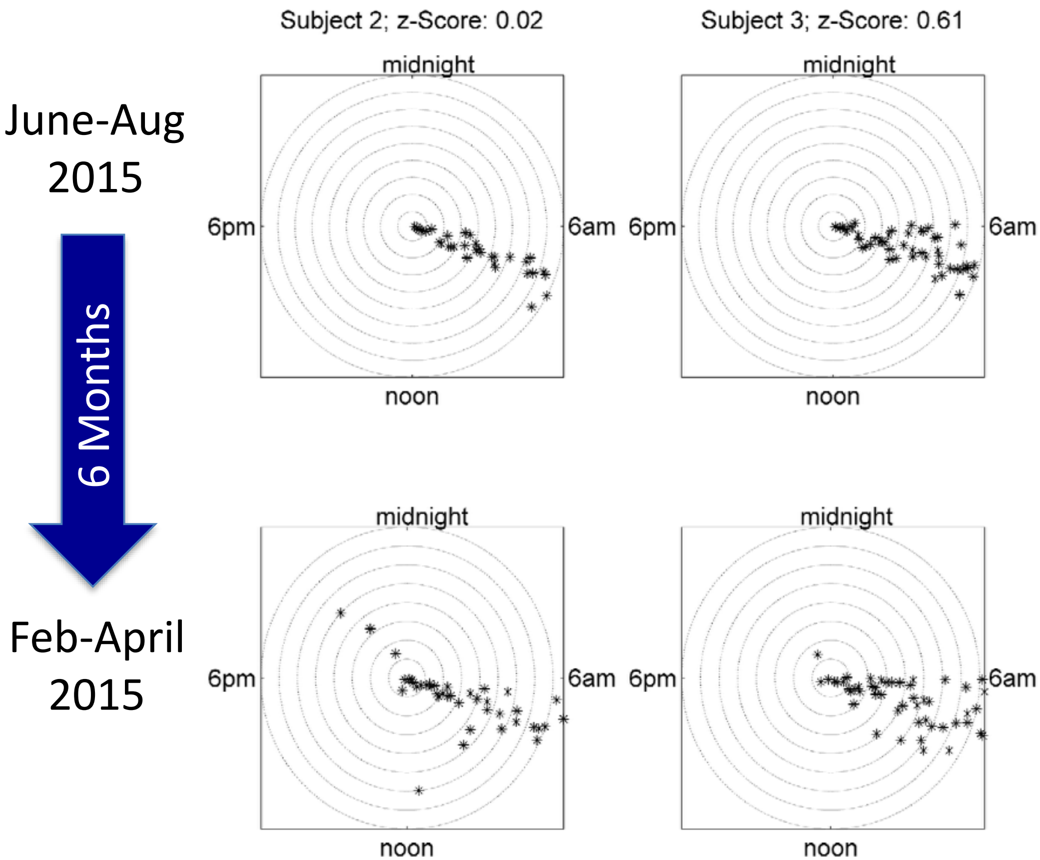
Abstract

Go to:

The relationship between recent episodes of poor sleep and cognitive testing performance in healthy cognitively intact older adults is not well understood. In this exploratory study, we examined the impact of recent sleep disturbance, sleep duration, and sleep variability on cognitive performance in 63 cognitively intact older adults using a novel unobtrusive in-home sensor based sleep assessment methodology. Specifically, we examined the impact of sleep the *night prior*, the *week prior*, and the *month prior* to a neuropsychological evaluation on cognitive performance. Results showed that mildly disturbed sleep the week prior and month prior to cognitive testing was associated with reduced working memory on cognitive evaluation. One night of mild sleep disturbance was not associated with decreased cognitive performance the next day. Sleep duration was unrelated to cognition. In-home, unobtrusive sensor monitoring technologies provide a novel method for objective, long-term, and continuous assessment of sleep behavior and other everyday activities that might contribute to decreased or variable cognitive performance in healthy older adults.

Cognition: Medication Adherence

Continuous monitoring of medication adherence may identify patients experiencing slow cognitive decline



- Individuals with lower cognitive function have more 'spread' in the timing of taking their medications ($p < .014$)
- Increase over time in the spread of timing of taking their medications ($P < .012$)

Austin, et al. Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring, 2017

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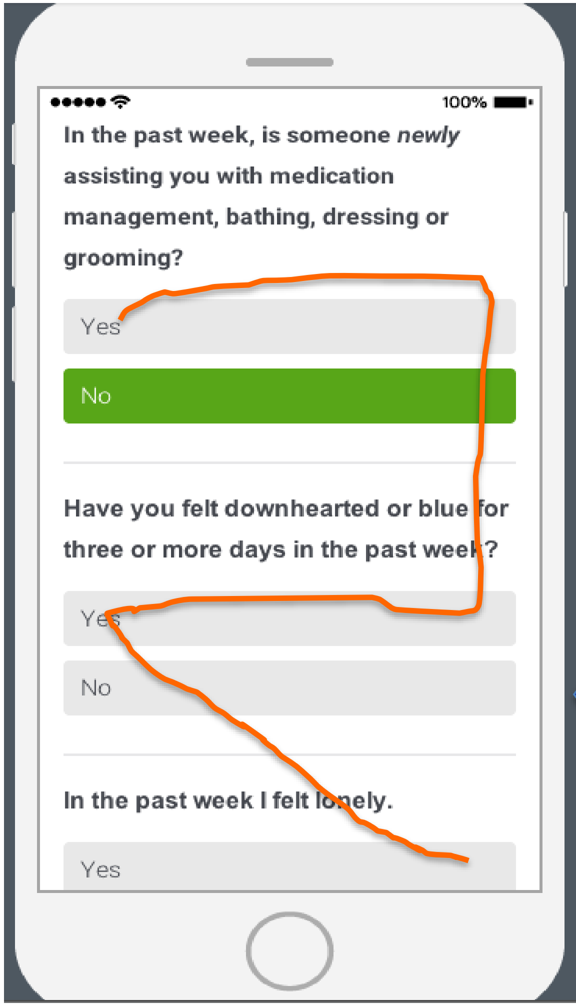
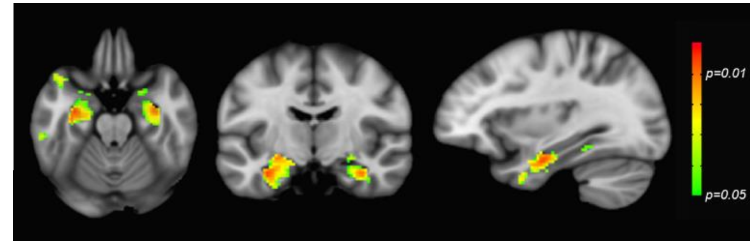
Computer Use: Assessment of Cognition, Behavior, Motor Function



Some Self-Report Data is Necessary



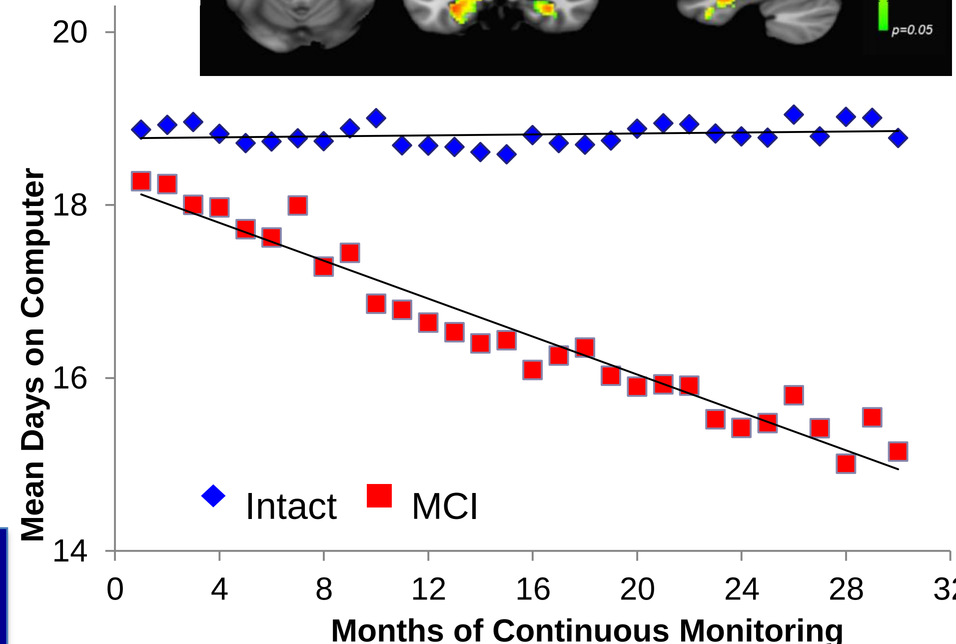


Table 4
Associations between cognitive status and mouse movement variability derived from one week of data

Covariate	Outcome, movement curvature (IQR_K) Coefficient	Outcome, movement curvature (IQR_K) *P* value	Outcome, time spent idling (IQR_Idle) Coefficient	Outcome, time spent idling (IQR_Idle) *P* value
MCI (reference: cognitively intact group)	0.013	.008**	386.8	.04*
Age (y)	−0.001	.03*	−15.0	.31
Education (y)	0.002	.05	−12.4	.70

Abbreviations: IQR, interquartile range; MCI, mild cognitive impairment.
NOTE. $*P < .05$, $**P < .01$.

Kaye, et al. Alzheimers Dement. 2014; Silbert et al., Alzheimers Dement, 2015; Seelye et al. Alzheimers Dement.: Diagnosis, Assessment & Disease Monitoring, 2015; Seelye et al. Alzheimer's Disease & Assoc. Disorders, 2015

Associations Between Observed In-Home Behaviors and Self-Reported Low Mood in Community-Dwelling Older Adults

Thielke, et al. Journal Amer Geriatr Soc., 2014

- *Every week* participants (n= 157; mean age 84) completed an online health questionnaire that assessed nine domains of health during the last week.
- The item related to low mood asked, "During the last week, have you felt downhearted or blue for more than three days?“
- 18,960 weekly observations of mood over 3.7 yrs were analyzed; 2.6% involved low mood.

Table 3. Coefficients from Generalized Estimating Equation Models for Within-Subject Differences in Behavior Parameters Between Weeks with Low Mood and Weeks without Low Mood

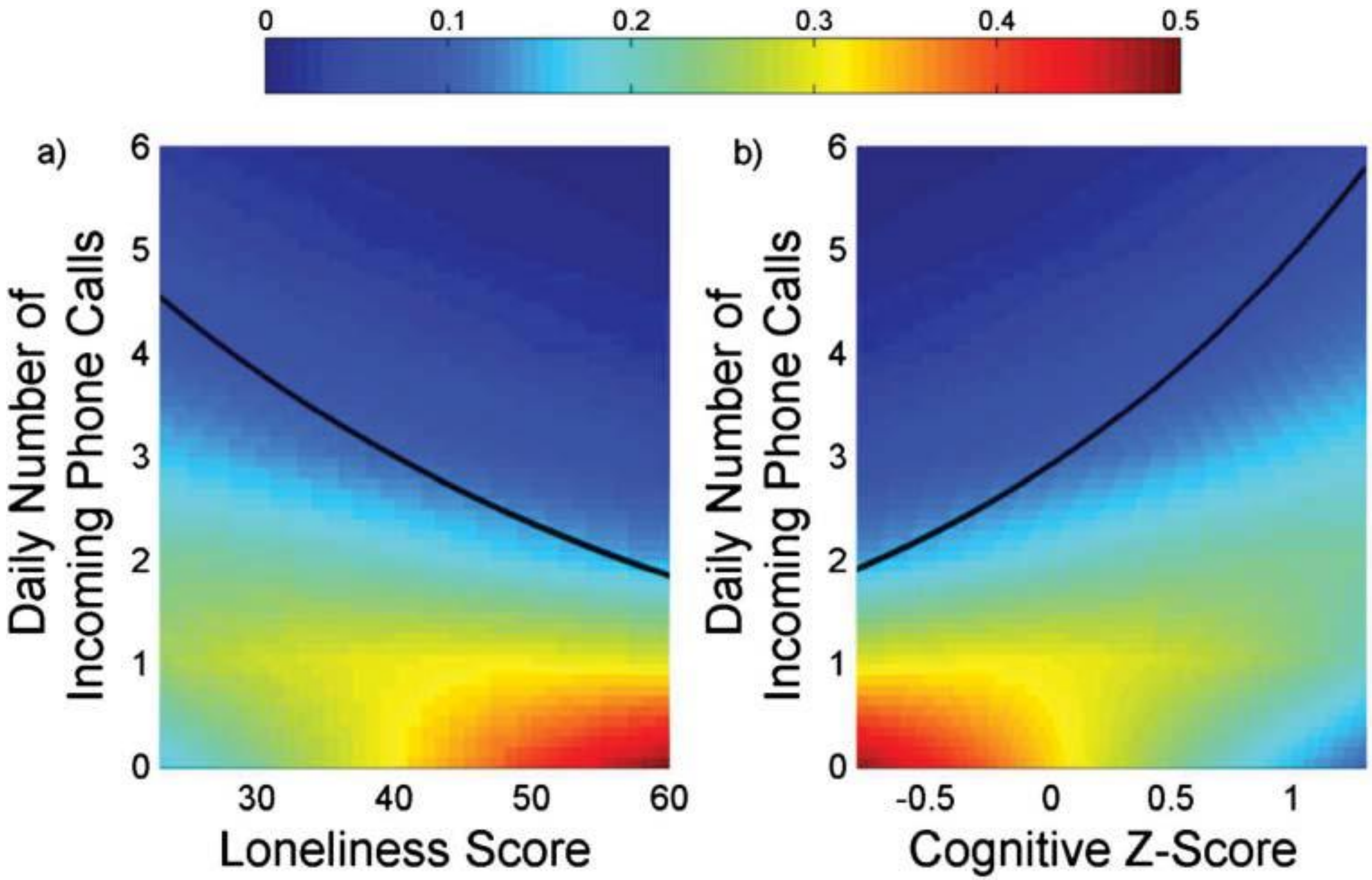
Behavior	Participants/Observations in Model	Difference (95% Confidence Interval) During Low Mood Week,%	Estimated Difference in Parameter	*P*-Value
Walking speed	83/8,027	−1% (−3–1%)	−0.6 cm/s	.35
Time out of residence	84/8,427	−9% (−15 to −3%)	−24 min/d	.007
Room transitions	54/3,977	−3% (−7–2%)	−0.3 per hour	.31
Computer use	67/8,640	−13% (−20 to −4%)	−10 min/d	.004

Models adjusted for sex, age, chronic disease score at baseline, and individual's mean value of the behavior parameter during the observation period. The coefficients represent the percentage difference in the parameter between weeks when low mood was reported and weeks when low mood was not reported. The estimated difference in the parameter represents the absolute numerical difference in each of the outcomes between weeks when low mood was reported and weeks when low mood was not reported.

Phone use

Indicator of mood and cognitive function

22,595 calls; 26 people; 25 weeks



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Petersen et al. Phone behaviour and its relationship to loneliness in older adults, Aging & Mental Health, 2016

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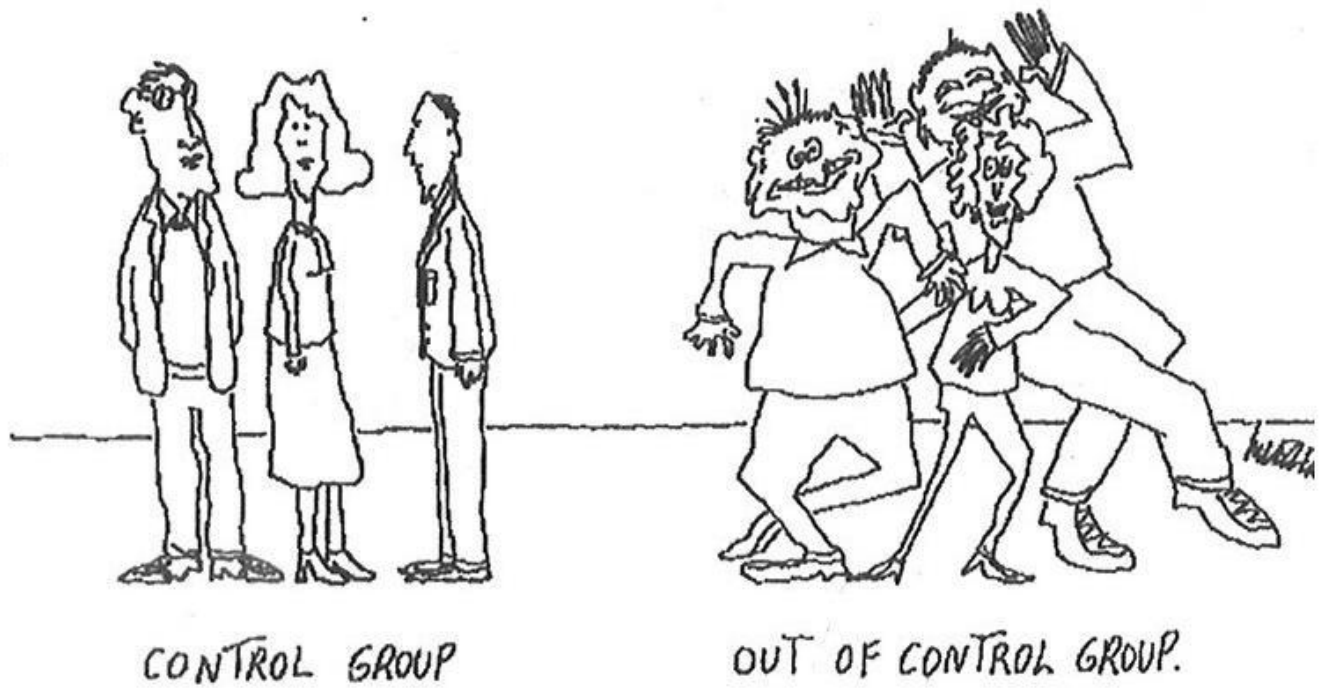
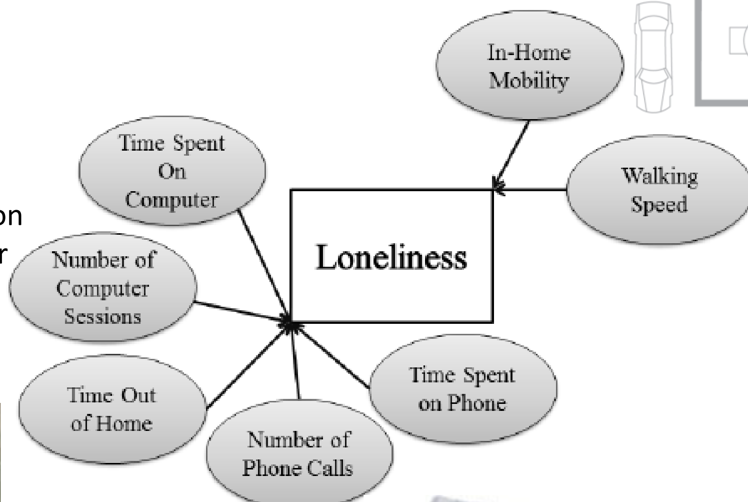
Considering Trials

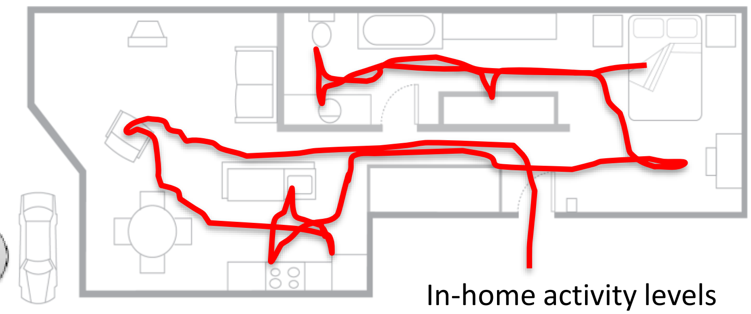


Using objective in-home monitoring to identify meaningful behaviours changing during a loneliness intervention

Intervention: "Capturing Time: Journaling Your Journey" -- designed to improve negative emotions such as loneliness, depression, anxiety, and low self-esteem.

Computer use (time on computer; computer sessions)

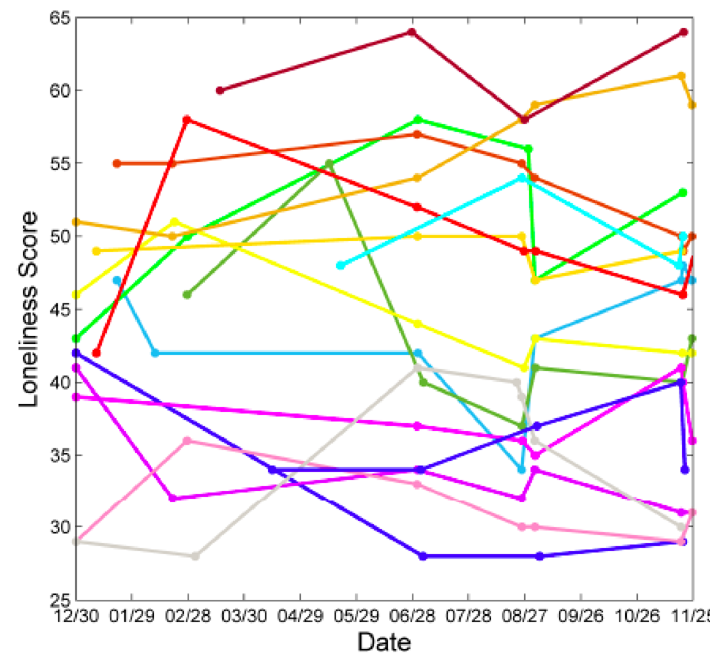




In-home activity levels (mobility, walking speed)

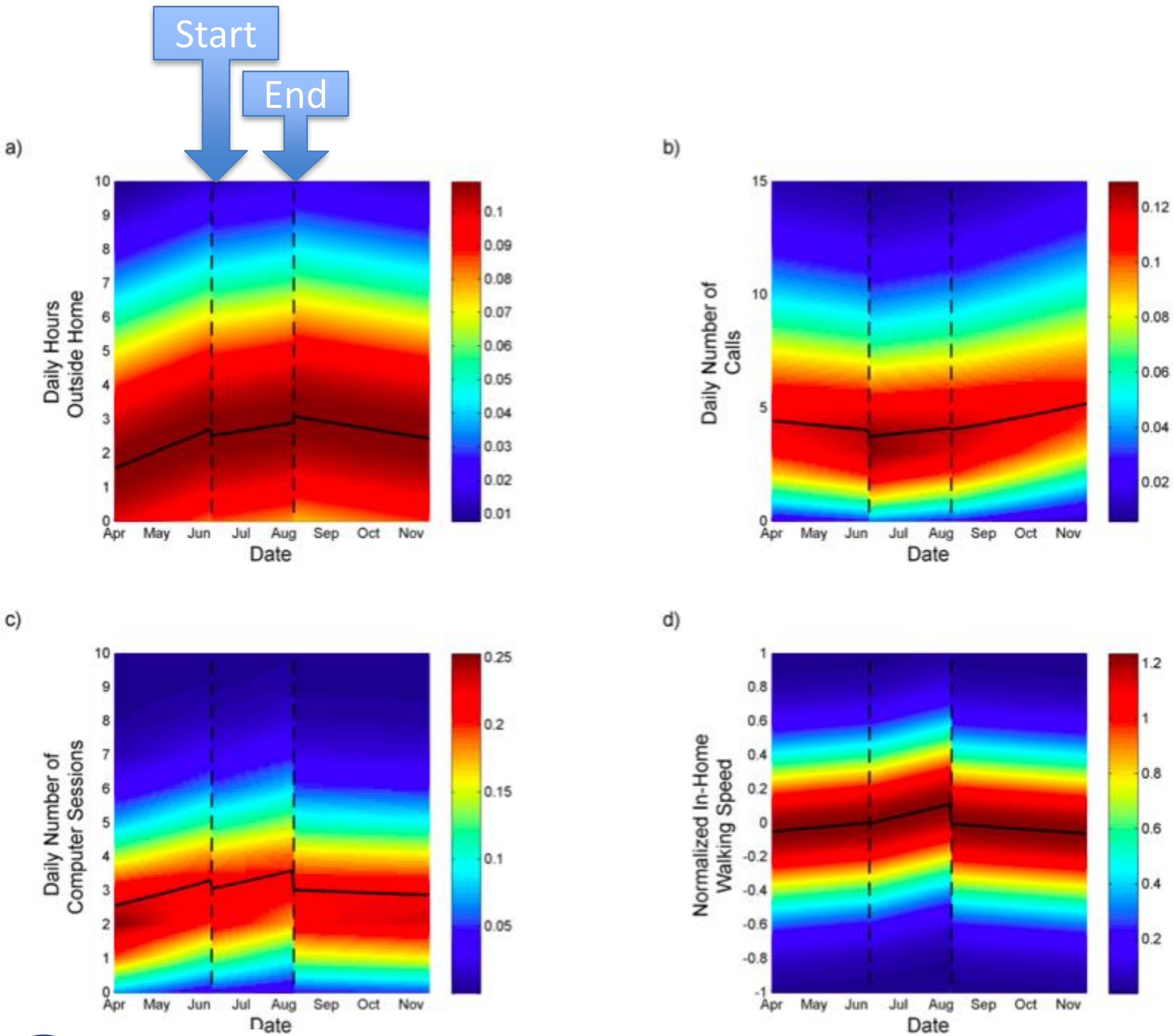
Time spent outside home

Phone use (time on phone; number of calls



Austin et al. IEEE Journal of Translational Engineering in Health Medicine 2016

Capturing Time: digital biomarker results



- ↓ Loneliness ($p<0.05$) by an average of 2.2 ± 3 points.
- ↑ Time out-of-home ($\beta=0.96$, $p<0.01$)
- ↑ Number of computer sessions (IRR=1.196, $p<0.01$)
- ↓ Daily number of calls (IRR=0.84, $p<0.05$).
- ↑ Total phone calls, after intervention (IRR=1.003, $p<0.01$)
- ↑ Walking speed over time ($\beta = 0.002$, $p<0.01$).

Austin, et al. 2017 (under review)

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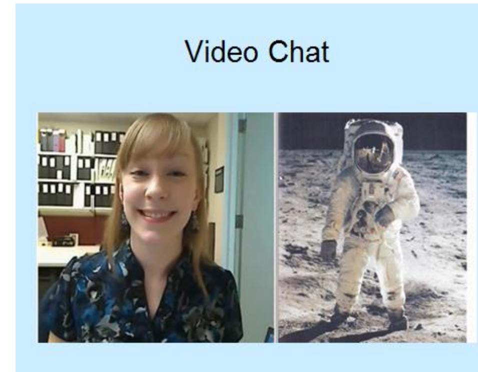
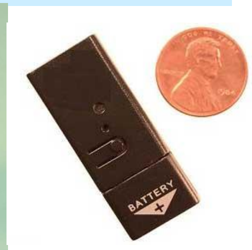
The "Social Engagement Study" (H. Dodge, PI)

Active, Frequent Assessments & Interventions Can be Delivered Everyday - *an RCT to Increase Social Interaction in MCI Using Home-based Technologies*



- 6 week RCT of daily 30 min video chats using Internet connected personal computers with a webcam vs. weekly brief phone interview
- N = 86; 80.5 ± 6.8 years; MCI & Normal Cognition
- 89% of all possible sessions completed; Exceptional adherence – no drop-out
- MCI participants spoke 2985 words on average; cognitively intact spoke 2423 words during sessions (controlling for age, gender, interviewer and time of assessment, p=0.03)



Dodge et al. Alzheimer's & Dementia: Translational Research & Clinical Interventions, 2015
Dodge et al., Current Alzheimer's Disease, 2015

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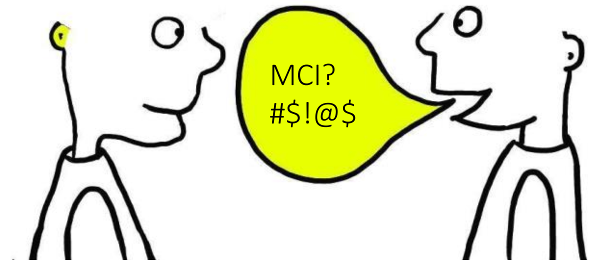
Social Engagement Study

Social markers of cognitive function

LIWC cat.	Communication	Swear	Anger	Fillers	Family
Avg. num. in MCI	46.4	7.14	37	101.5	31.14
Avg. num. in intact	38.7	4.8	49.8	141.6	41.8
p-value	0.002	0.005	0.054	0.067	0.08

Table 4: Average number of words grouped into LIWC categories



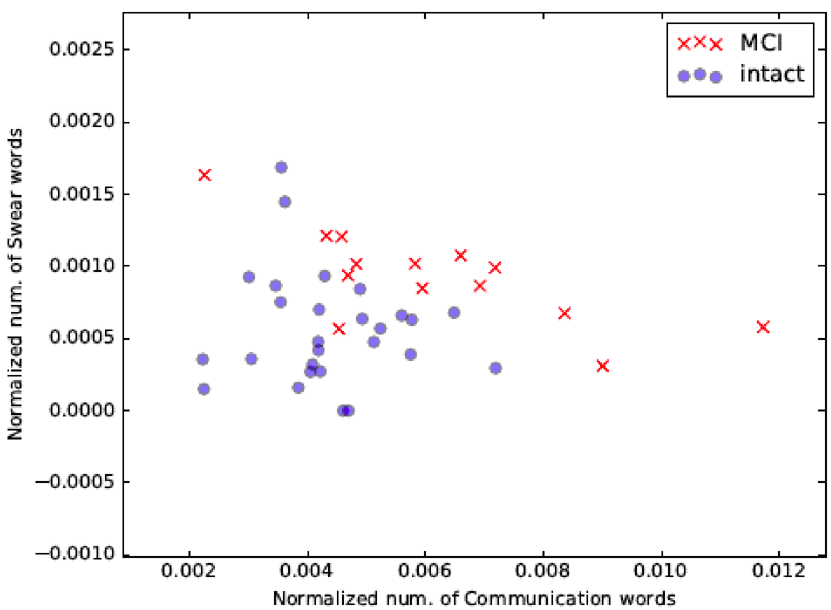


Figure 1: scatter-plot of features derived from Communication and Swear word categories

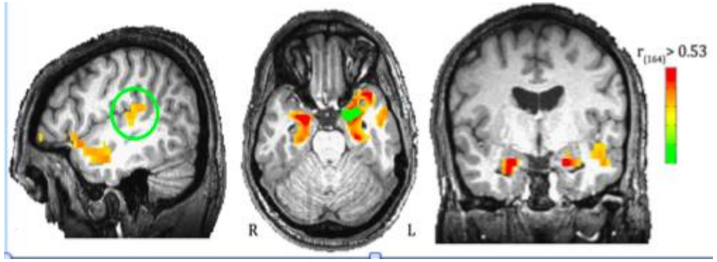
Dodge et al. Current Alzheimer Res. 2015

Asgari et al. Alzheimer's & Dementia: Translational Research & Clinical Interventions, 2017

I-CONECT: *Internet-based Conversational Engagement Clinical Trials*

PI: H. Dodge

NIA R01AG051628; R56AG056102)



Isolated 80+ yrs, 50% African American

OHSU

MCI n=90 → TX n=45; Control n=45

Healthy n=90 → TX n=45; Control n=45

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MCI n=90 → TX n=45; Control n=45

Healthy n=90 → TX n=45; Control n=45

TX: Video Chat, 4 times/week: 6 months, 2 times/ week: 6 months

Control: 1/wk phone check. Novel Outcome Measures: MedTracker memory, Conversational Speech & Language Quantification; vMRI, DTI, fMRI

ADCS PEACE-AD: RCT of Prazocin for Agitation in AD

Biometric Monitoring Devices (BMDs) Assessing Agitation

Digital Agitation Assessment -

Wrist-worn devices with long battery life, H_2O-proof and pulse measurement. Activity levels monitored continuously during entire 12-week titration study using wrist actigraphy. Continuous monitoring critical as study employs a flexible dose titration schedule, and the use of rescue medication for agitation (lorazepam).

Outcome measures -

Motor activity (total activity counts/steps over a 24 hour period (MA_{24}), and the 12 hour period from 6 PM to 6 AM for each wk (MA_{12}), for the 12 wk study. Percent change in total activity counts at wk 1 (pre-TX) compared to wk 12 (post-TX) will be calculated (DMA_{24} and DMA_{12}).

Exploratory analyses -

Value of heart rate with movement metrics, activity counts in subjects receiving lorazepam and in those discontinuing prazosin. Sleep disruption/continuity.

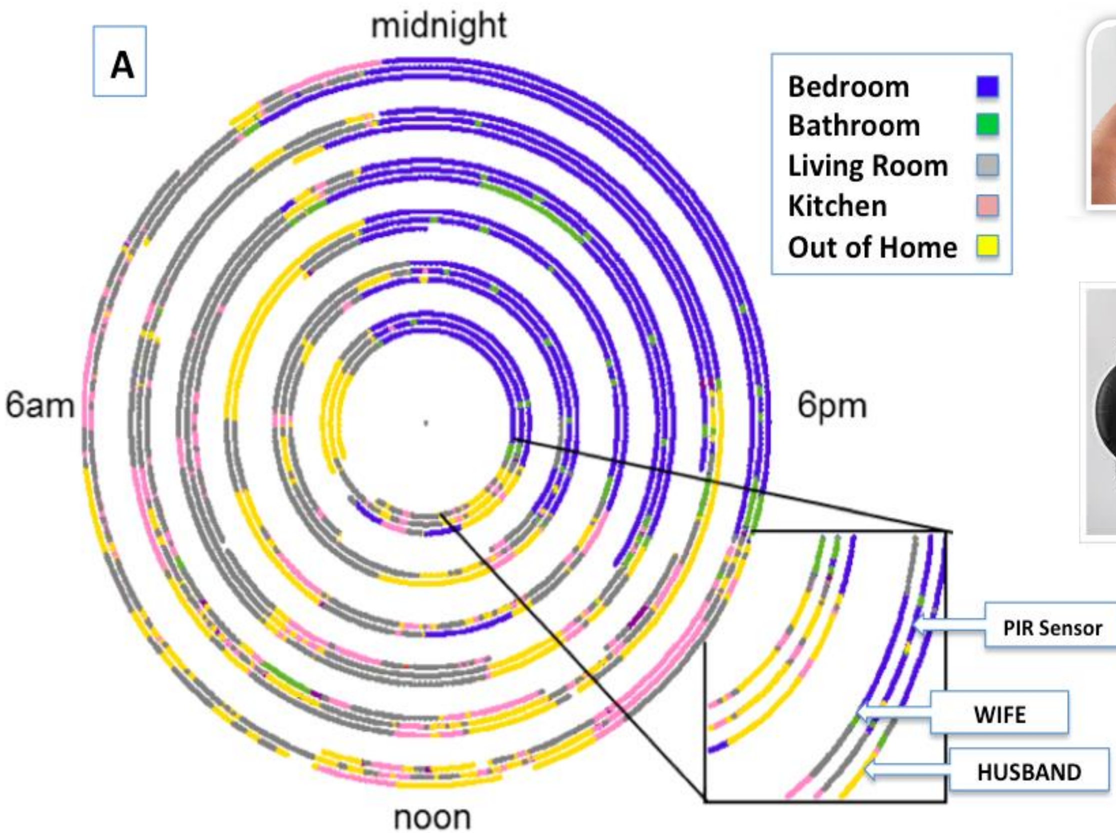
EVALUATE - AD

Ecologically Valid, Ambient, Longitudinal and Unbiased Assessment of Treatment Efficacy in Alzheimer's Disease

- Longitudinal naturalistic observational cohort study spanning up to 18 months
- Goal: Establish Digital Biomarkers that are sensitive to clinical change associated with conventional AD TXs
- ORCATECH platform
- Sixty subjects: 30 patients/30 care partners (30 households)
- NIA / Merck Funding

Core Functions & Measures	Sensors or Devices Used	Conventional Assessment Measures
Physical Capacity/Personal Mobility Total daily activity, number of room transitions, median weekly walking speed from multiple daily walks, daily steps, time out of home	PIR motion sensors and contact sensors; Actigraphy	Walking speed (with stopwatch). Self-report of activity from OADC Personal & Family History Questionnaire (Paffenbarger scale, e.g., *estimate hours per day you spent in low activity*)
Sleep/Nighttime behavior Time of awakening, time spent in bed at night, wake after sleep onset, times up at night, and sleep latency	PIR motion sensors; Actigraphy	Pittsburgh Sleep Quality Index and Sleep Disturbance Symptom Questionnaire (OADC Personal & Family History Questionnaire)
Physiologic Health Daily BMI, pulse, arterial resistance	Biofunction Scale (AM pulse, art. resistance); Actigraph pulse	Vital signs (height, weight, pulse)
Medication Adherence Percentage of doses missed in a 7-day period, relative to prescribed schedule.	MedTracker Electronic Pillbox	Self-report of adherence to medication taking regimen (visual-analogue scale: ranging from zero to 100%)
Socialization/Engagement Time out of home, time alone or with spouse, phone call patterns, on-line computer activity (email, social network sites)	PIR motion sensors, contact sensors, actigraphy, personal computer, phone monitors	Self-report of 8 social activities from OADC Personal & Family History Questionnaire (e.g., how often do you have visitors: rarely/never, daily, weekly, monthly. yearly)
Cognitive Function Time to complete on-line tasks (e.g., weekly PHAR), mouse movements, prospective memory for medication, AM weighing protocol.	Personal computer or tablet, MedTracker, Biofunction scale.	Z-score composite of UDS cognitive battery; ADAS-cog 13 score.
Community Mobility – Driving Time and distance driving, hard braking, hard accelerations, most frequent locations out of home	Home sensors (exit door contact sensors); Automobile data port telematic sensor	FAQ rating of ability: *Traveling out of neighborhood, driving, arranging to take buses*
Health & Life Events On-line self-report: ER, doctor, hospital visits, home visitors, mood, pain, loneliness, falls, injuries, change in home space, home assistance received, change in medications	Personal computer or tablet (On-line reporting)	Mood: Geriatric Depression Scale (15 item) and Neuro- Psychiatric Inventory (NPI); Self-report of health events from OADC Personal & Family History Questionnaire
Care Partner Engagement Time alone/time with cognitively impaired partner; time in bathroom together	PIR motion sensors, contact sensors, actigraphy	Zarit Caregiver Burden scale – ZBI-12

EVALUATE – AD: Dyad Analysis



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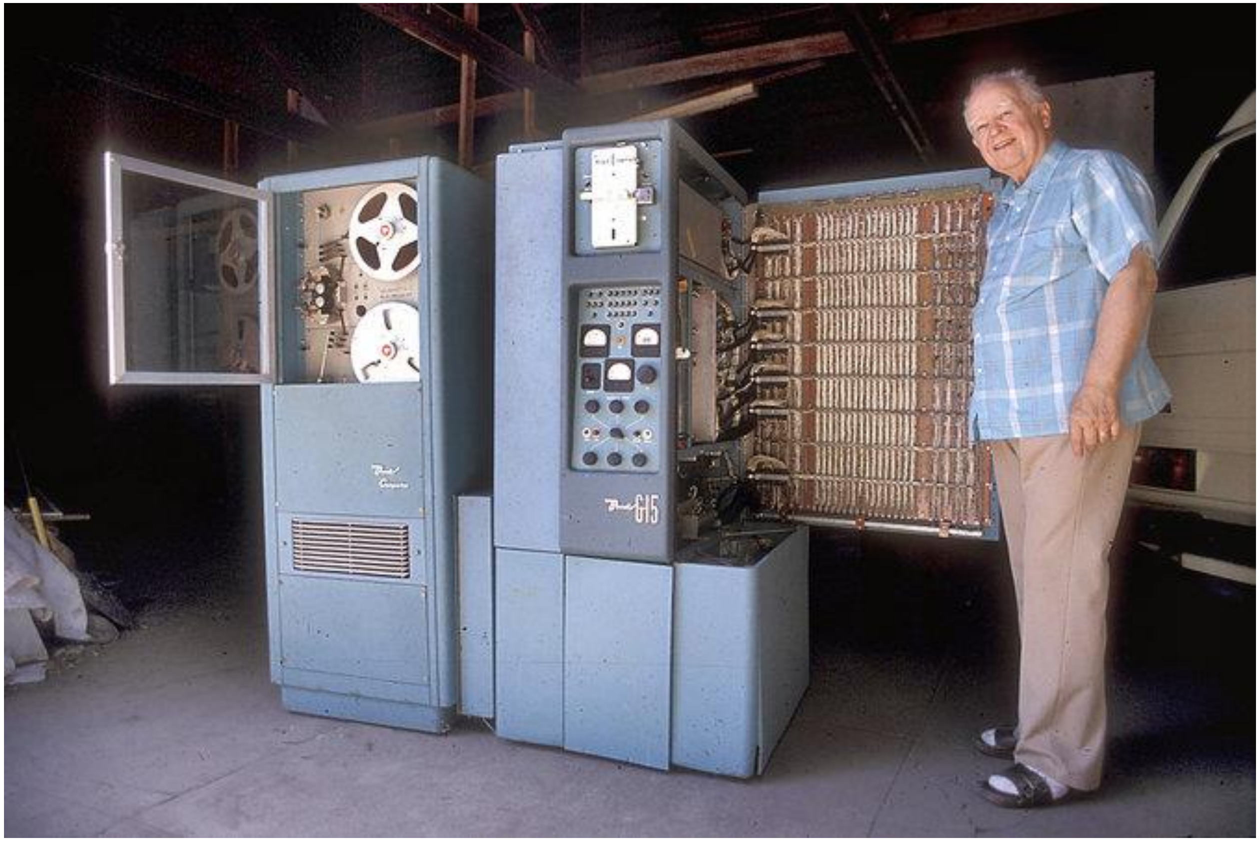
J. Austin, 2016, unpublished

Thank you!



Harry Huskey (1916 – 2017)

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kaye@ohsu.edu

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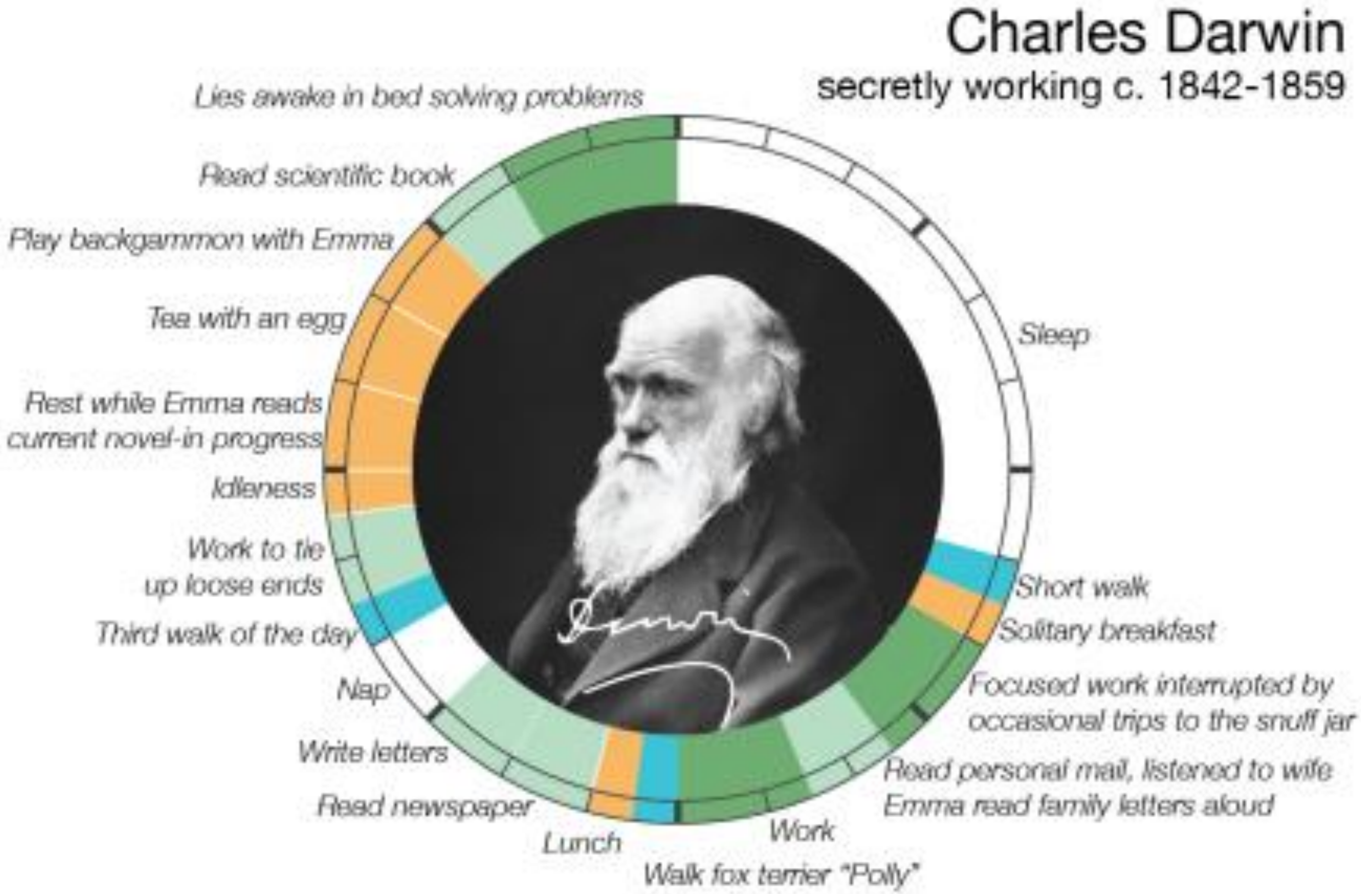
Identifying Prodromal Markers:

The Everyday Cognition and Functional Activity Life Cycle



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http://infowetrust.com/2014/03/26/creative-routines/

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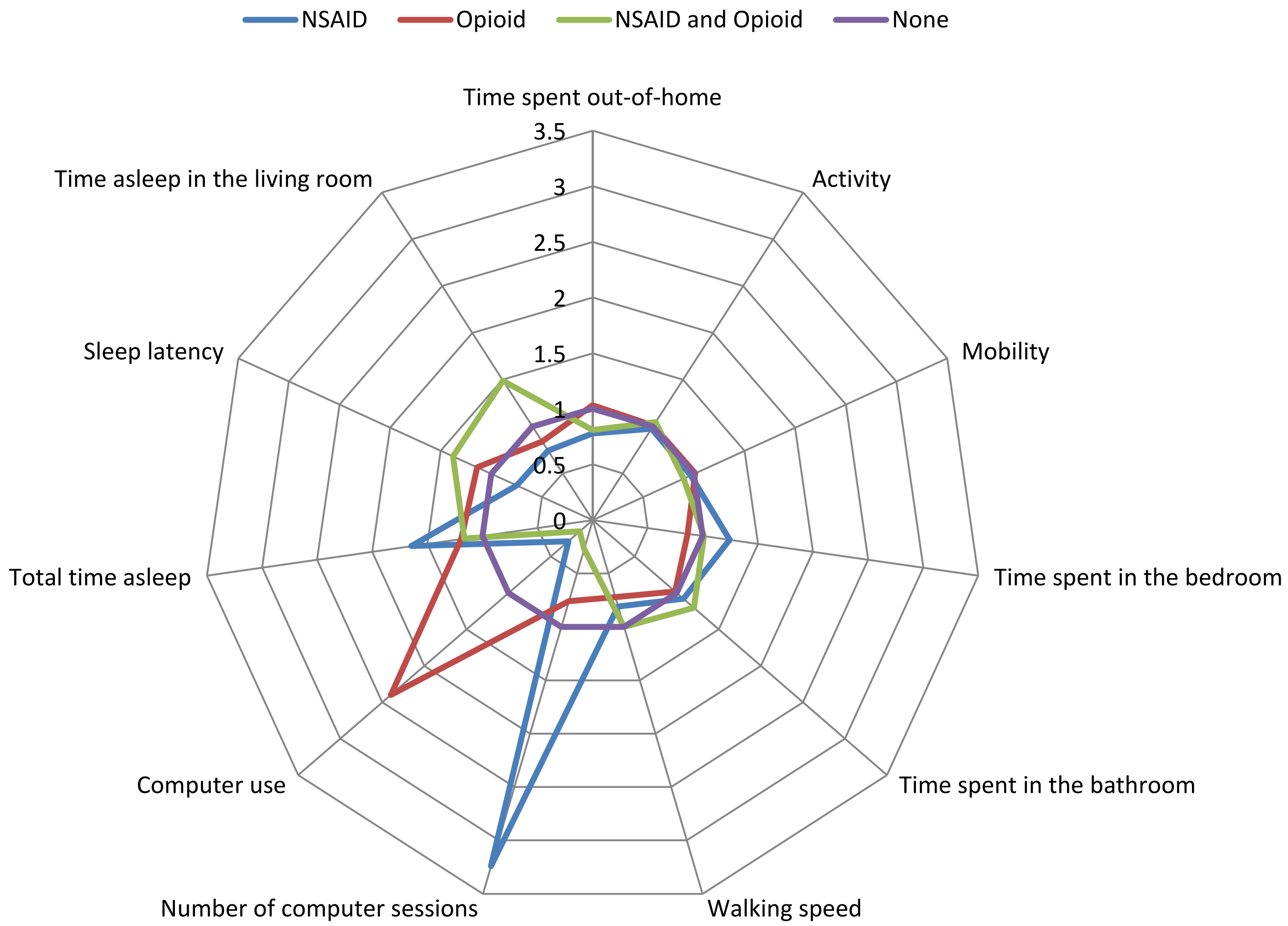
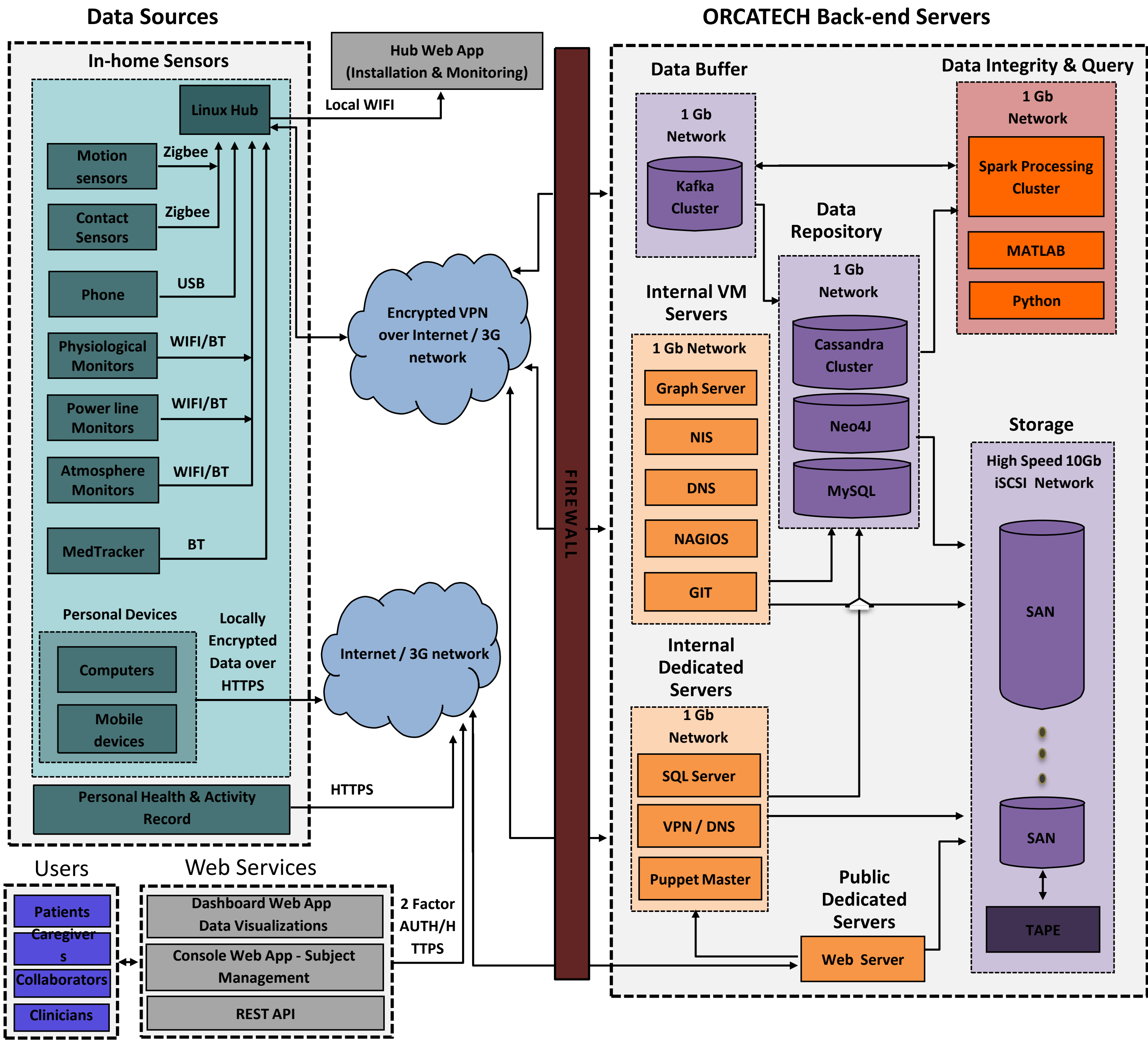
Behavioral Signature (Geometric Interpretation)



ORCATECH SYSTEM



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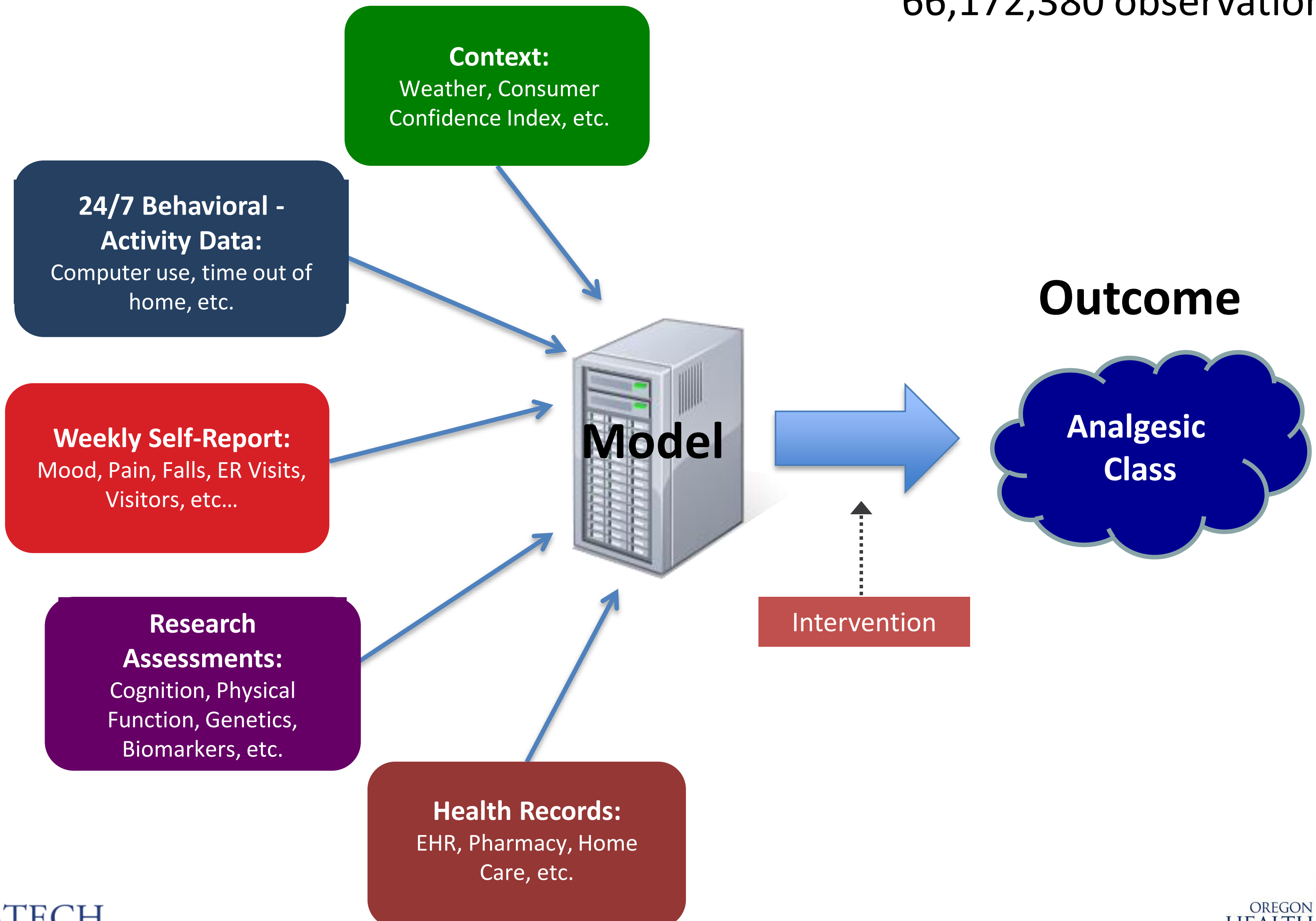
Putting it all together: High dimensional data fusion model predicting analgesic class

66,172,380 observations



Austin et al. 2015

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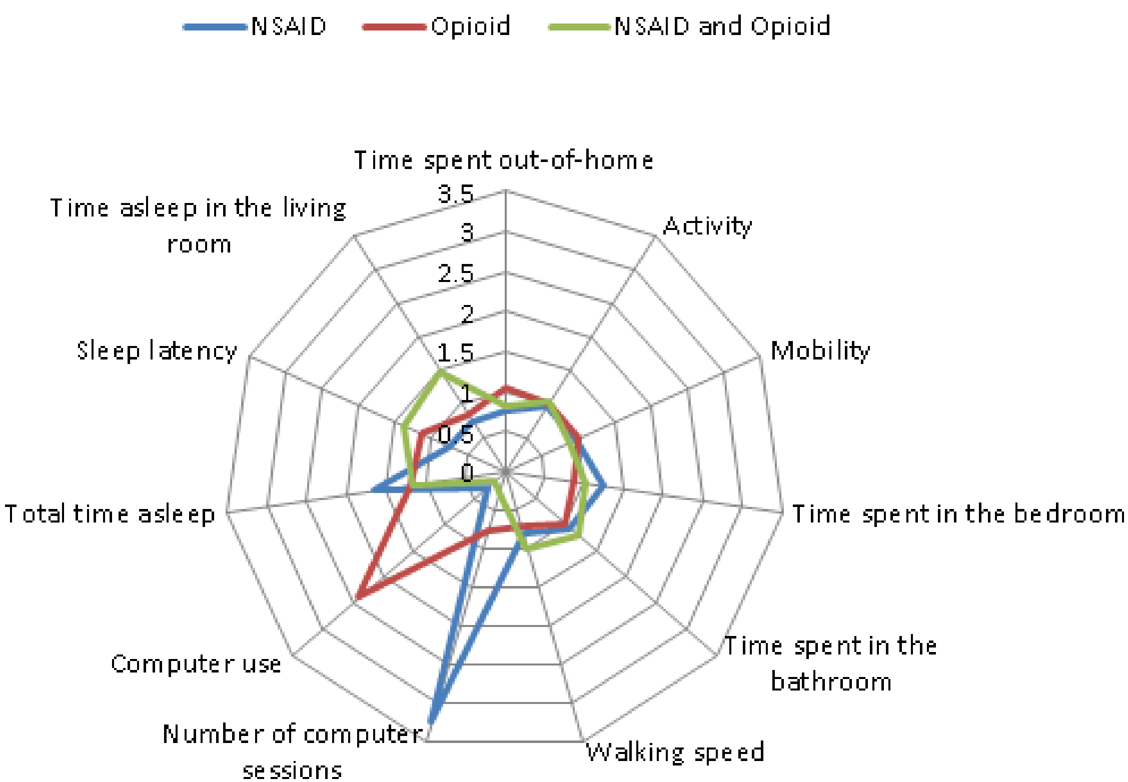
Predicting Drug Class Effects: Case of analgesics



	NSAID	Opioid	Both
Sensitivity (%)	94.9	65.9	67.4
Specificity (%)	99.9	98.6	99.6
Positive Predictive Value (%)	99.7	82.6	86.1
Negative Predictive Value (%)	99.7	96.6	98.9
Correctly Classified (%)	99.6	95.6	98.6

Logistic regression models treated as classifiers (and model fit statistics)

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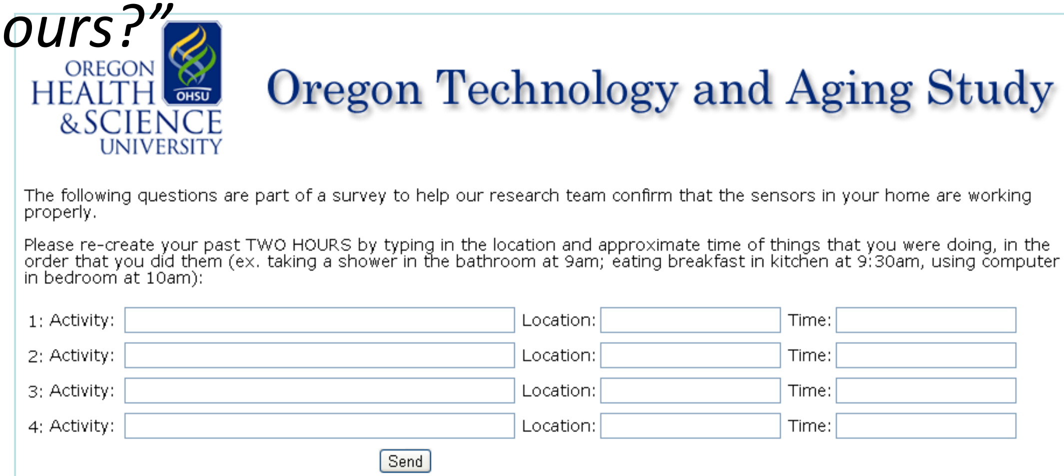
Observation period: July 2011 – March of 2014; 66,172,380 observations

Challenge of Detecting Change: Self Report Inaccuracy

Are you sure?: Lapses in Self-Reported Activities Among Healthy Older Adults Reporting Online. Wild et al., 2015

"What were you doing during the past 2 hours?"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Oregon Technology and Aging Study

The following questions are part of a survey to help our research team confirm that the sensors in your home are working properly.

Please re-create your past TWO HOURS by typing in the location and approximate time of things that you were doing, in the order that you did them (ex. taking a shower in the bathroom at 9am; eating breakfast in kitchen at 9:30am, using computer in bedroom at 10am):

1: Activity: Location: Time:
2: Activity: Location: Time:
3: Activity: Location: Time:
4: Activity: Location: Time:

Send

- 26% *No Match Between Sensors & Report*
- 49% Partial Agreement
- 25% Full Match

n=95; Mean age 84 yrs

Area	Firings	Time
Kitchen 1	1	0:00:00
Bedroom 1	14	0:01:52
Kitchen 1	1	0:00:00
Living Room 1	3	0:00:22
Living Room 1	1	0:00:00
Bathroom 2	1	0:00:00
Living Room 1	1	0:00:00
Kitchen 1	1	0:00:00
Bedroom 1	4	0:01:12
Kitchen 1	5	0:00:33
Living Room 1	1	0:00:00
Kitchen 1	1	0:00:00
Living Room 1	1	0:00:00
Kitchen 1	1	0:00:00
Bedroom 1	1	0:00:00
Kitchen 1	1	0:00:00
Bedroom 1	1	0:00:00
Kitchen 1	10	0:01:03
Living Room 1	1	0:00:00
Kitchen 1	1	0:00:00
Living Room 1	1	0:00:00
Computer Room	3	0:00:14

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