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
High Interest in Digital Technologies

**CART --** Collaborative Aging (in Place)
- Interagency initiative with NIA, NIBIB, NCI, NINDS, NINR, NIBIB

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### $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 the University of Colorado, University of Virginia, Clemson University, and University of Washington.

**BOOKMARK THE PERMALINK.**

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### NEWSROOM

**NIH initiative tests in-home technology to help seniors age in place**

January 25, 2017

Many older adults want to live at home independently as they age. Sometimes, their families and friends—and the right technology. A new initiative led by the National Institute on Aging (NIH) aims to help seniors age in place by developing a research platform that can 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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### ALL OF US RESEARCH PROGRAM

#### All of Us Research Program

- **Scale and Scope**
- **Participation**
- **Program Components**
- **Funding**
- **FAQ**
- **Advisory Groups**
- **Events**
- **Announcements**
- **In the News**
- **Multimedia**

#### 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 webcast at the Intel Corporation campus in Santa Clara, California, and is being held.

This workshop is based on the unique scientific questions developed during the April 28-29 workshop. Clinical data sets are shared during the May 28-29 workshop, and
Why Biomarkers?

Progression of biomarkers in AD Progression

“Clinical markers are insensitive and change late”

Instrumental activities of daily living: a stepping-stone towards diagnosis in subjects with impairment?


This paper challenges the requirements of normal activities of daily living/instrumental activities of daily living (ADL/IADL) in mild cognitive impairment and stresses the need for further research.

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

Katrin Jekel1,2*, Marinella Damian2, Carina Wattmo3, Lucrezia Hausner2, Roger Bullock4, Peter J Connelly5, Bruno Dubois6, Maria Eriksdotter7, Michael Ewers8, Elmar Graesel9, Milica G Kramberger10, Emma Law11, Patrizia Mecacci12, José L Molinuevo13, Louise Nygård14, Marcel GM Olde Rikkert15, Jean-Marc Orgogozo16, Florence Pasquier17, Karine Peres18,19, Eric Salmon20, Sietske AM Sikkes21, Tomasz Sobow22, René Spiegel23, Maresa Tsokas24, René Winkler25, and Lutz Fröhlich2

RESEARCH Open Access

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.
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
High variability in self-report measures -- UCLA Loneliness Scale

Austin et al. Smart-Home System to Unobtrusively and Continuously Assess Loneliness in Older Adults. IEEE Journal of Translational Engineering in Health Medicine, 2016
Which has brought us to BDMs in Trials...

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

Pervasive Computing
Wireless Technologies
“Big Data” Analytics

Measured Function
Baseline 12 Mos 24 Mos

EVIDENCE

?
Evidence for Use of BMDs in (Dementia) Trials

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


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.
Evidence for Use of BMDs in Dementia Trials


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

<table>
<thead>
<tr>
<th></th>
<th>SMARTPHONES/PDAS</th>
<th>WEARABLE DEVICES</th>
<th>BIOSENSOR DEVICES</th>
<th>COMPUTERIZED SYSTEM</th>
<th>MULTIPLE COMPONENTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of studies, N=62, n (%)</td>
<td>12 (19)</td>
<td>11 (18)</td>
<td>7 (11)</td>
<td>6 (10)</td>
<td>26 (42)</td>
</tr>
<tr>
<td>Country, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-U.S.²</td>
<td>6 (50)</td>
<td>7 (64)</td>
<td>5 (71)</td>
<td>2 (33)</td>
<td>16 (62)</td>
</tr>
<tr>
<td>U.S.</td>
<td>6 (50)</td>
<td>4 (36)</td>
<td>2 (29)</td>
<td>4 (67)</td>
<td>10 (38)</td>
</tr>
<tr>
<td>Disease category, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cancer</td>
<td>1 (8)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cardiovascular</td>
<td></td>
<td>3 (27)</td>
<td>3 (43)</td>
<td></td>
<td>5 (19)</td>
</tr>
<tr>
<td>Metabolic disorders</td>
<td>2 (17)</td>
<td>1 (9)</td>
<td>1 (14)</td>
<td></td>
<td>6 (23)</td>
</tr>
<tr>
<td>Neurological</td>
<td>1 (8)</td>
<td>4 (36)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Psychological</td>
<td>2 (17)</td>
<td>1 (9)</td>
<td></td>
<td></td>
<td>1 (17)</td>
</tr>
<tr>
<td>Respiratory</td>
<td>2 (17)</td>
<td></td>
<td>2 (29)</td>
<td>1 (17)</td>
<td>9 (35)</td>
</tr>
<tr>
<td>Sleep disorders</td>
<td></td>
<td>2 (18)</td>
<td></td>
<td></td>
<td>1 (4)</td>
</tr>
<tr>
<td>Substance abuse</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1 (4)</td>
</tr>
<tr>
<td>Weight management</td>
<td></td>
<td></td>
<td></td>
<td>4 (67)</td>
<td>3 (12)</td>
</tr>
<tr>
<td>Other/Multiple³</td>
<td></td>
<td></td>
<td>1 (14)</td>
<td></td>
<td>1 (4)</td>
</tr>
<tr>
<td>Age category, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;20 years old</td>
<td>1 (8)</td>
<td>1 (9)</td>
<td></td>
<td></td>
<td>1 (4)</td>
</tr>
<tr>
<td>21–39 years old</td>
<td>1 (8)</td>
<td>2 (18)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>40–64 years old</td>
<td>3 (25)</td>
<td>2 (18)</td>
<td>2 (29)</td>
<td>1 (17)</td>
<td>3 (12)</td>
</tr>
<tr>
<td>≥65 years old</td>
<td>1 (8)</td>
<td>1 (9)</td>
<td></td>
<td></td>
<td>4 (15)</td>
</tr>
<tr>
<td>&gt;20 years old³</td>
<td>6 (50)</td>
<td>4 (36)</td>
<td>5 (71)</td>
<td>5 (83)</td>
<td>18 (69)</td>
</tr>
<tr>
<td>Not reported</td>
<td>1 (9)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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


Studies Cohorts
- Life Laboratory Cohort
- Life Laboratory - BC
- AIMS Transitions
- EVALUATE - AD
- iCONECT - MI/OR
- CART - 202 Portland
- CART - VA VISN 20
- CART - MARS Chicago
- CART - PRISM Miami
- ACTC Studies XYZ

Device / Sensor “X”
- Body Composition, Pulse, Temperature, CO₂
- MedTracker
- Secure Internet
- ORCATECH Secure Data Backend
  - Digital Data Repository

Data Scientists
- University Collaborations
- PHARMA
- Health Industry

ORCATECH
- Sensing Life Kinetics

EVALUATE
- AD

AIMS Transitions

Life Laboratory Cohort

Life Laboratory - BC

EVALUATE - AD

iCONECT - MI/OR

CART - 202 Portland

CART - VA VISN 20

CART - MARS Chicago

CART - PRISM Miami

ACTC Studies XYZ

Phone Activity/EMA

Driving

Doors Open/Close

Computer Activity

Secure Internet

Data Scientists

University Collaborations

PHARMA

Health Industry

Considering Use Examples
Emphasizing Motor Function, Sleep, and Cognition

"Don’t panic. It's only a prototype."
Physical Activity and Mobility Behaviors

Differentiation of early MCI

Activity patterns associated with MCI

Trajectories of gait speed over time

Early MCI
Late MCI
Physical Activity and Mobility Behaviors

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

<table>
<thead>
<tr>
<th>Room</th>
<th>Bedroom</th>
<th>Bathroom</th>
<th>Kitchen</th>
<th>Living Room</th>
<th>Combined</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_{0.5}$ Score*</td>
<td>0.842</td>
<td>0.829</td>
<td>0.813</td>
<td>0.826</td>
<td>0.856</td>
</tr>
</tbody>
</table>

*F_{0.5}$ Scores window size $\omega = 20$ 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**

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

### No Differences Between Groups in Self-Report Measures

<table>
<thead>
<tr>
<th>Self-Report Measure</th>
<th>Intact</th>
<th>aMCI</th>
<th>naMCI</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subjective Daytime Sleep</td>
<td>1.8 ± 0.2</td>
<td>1.5 ± 0.3</td>
<td>2.0 ± 0.3</td>
<td>0.69</td>
</tr>
<tr>
<td>Insomnia</td>
<td>1.3 ± 0.2</td>
<td>0.8 ± 0.3</td>
<td>1.6 ± 0.3</td>
<td>0.21</td>
</tr>
<tr>
<td>Restlessness</td>
<td>1.0 ± 0.1</td>
<td>0.4 ± 0.3</td>
<td>0.7 ± 0.2</td>
<td>0.34</td>
</tr>
<tr>
<td>Times up at night</td>
<td>1.1 ± 0.1</td>
<td>1.0 ± 0.3</td>
<td>1.0 ± 0.2</td>
<td>0.77</td>
</tr>
</tbody>
</table>

Cognition: Computer/Internet-based Online Testing
Survey for Memory, Attention, and Response Time (SMART)

Face-valid cognitive tasks
Mouse/touchscreen movements

Movement hesitation = “thinking time”

Typing speed
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 Kaye¹ ² ³

Abstract

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
Computer Use: Assessment of Cognition, Behavior, Motor Function

Some Self-Report Data is Necessary

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

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

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

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

Capturing Time: digital biomarker results

- ↓ Loneliness (p<0.05) by an average of 2.2 ± 3 points.
- ↑ Time out-of-home (β=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 (β = 0.002, p<0.01).

Austin, et al. 2017 (under review)
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., Current Alzheimer’s Disease, 2015
Social Engagement Study

Social markers of cognitive function

<table>
<thead>
<tr>
<th>LIWC cat.</th>
<th>Communication</th>
<th>Swear</th>
<th>Anger</th>
<th>Fillers</th>
<th>Family</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. num. in MCI</td>
<td>46.4</td>
<td>7.14</td>
<td>37</td>
<td>101.5</td>
<td>31.14</td>
</tr>
<tr>
<td>Avg. num. in intact</td>
<td>38.7</td>
<td>4.8</td>
<td>49.8</td>
<td>141.6</td>
<td>41.8</td>
</tr>
<tr>
<td>p-value</td>
<td>0.002</td>
<td>0.005</td>
<td>0.054</td>
<td>0.067</td>
<td>0.08</td>
</tr>
</tbody>
</table>

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)

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, H₂O-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 (MA₂₄), and the 12 hour period from 6 PM to 6 AM for each wk (MA₁₂), 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 (DMA₂₄ and DMA₁₂).

**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

<table>
<thead>
<tr>
<th>Core Functions &amp; Measures</th>
<th>Sensors or Devices Used</th>
<th>Conventional Assessment Measures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical Capacity/Personal Mobility</td>
<td>PIR motion sensors and contact sensors; Actigraphy</td>
<td>Walking speed (with stopwatch). Self-report of activity from OADC Personal &amp; Family History Questionnaire (Paffenbarger scale, e.g., estimate hours per day you spent in low activity)</td>
</tr>
<tr>
<td>Sleep/Nighttime behavior</td>
<td>PIR motion sensors; Actigraphy</td>
<td>Pittsburgh Sleep Quality Index and Sleep Disturbance Symptom Questionnaire (OADC Personal &amp; Family History Questionnaire)</td>
</tr>
<tr>
<td>Physiologic Health</td>
<td>Biofunction Scale (AM pulse, art. resistance); Actigraph pulse</td>
<td>Vital signs (height, weight, pulse)</td>
</tr>
<tr>
<td>Medication Adherence</td>
<td>MedTracker Electronic Pillbox</td>
<td>Self-report of adherence to medication taking regimen (visual-analogue scale: ranging from zero to 100%)</td>
</tr>
<tr>
<td>Socialization/Engagement</td>
<td>PIR motion sensors, contact sensors, actigraphy, personal computer, phone monitors</td>
<td>Self-report of 8 social activities from OADC Personal &amp; Family History Questionnaire (e.g., how often do you have visitors: rarely/never, daily, weekly, monthly, yearly)</td>
</tr>
<tr>
<td>Cognitive Function</td>
<td>Personal computer or tablet, MedTracker, Biofunction scale.</td>
<td>Z-score composite of UDS cognitive battery; ADAS-cog 13 score.</td>
</tr>
<tr>
<td>Community Mobility – Driving</td>
<td>Home sensors (exit door contact sensors); Automobile data port telematic sensor</td>
<td>FAQ rating of ability: Traveling out of neighborhood, driving, arranging to take buses</td>
</tr>
<tr>
<td>Health &amp; Life Events</td>
<td>Personal computer or tablet (On-line reporting)</td>
<td>Mood: Geriatric Depression Scale (15 item) and Neuro-Psychiatric Inventory (NPI); Self-report of health events from OADC Personal &amp; Family History Questionnaire</td>
</tr>
<tr>
<td>Care Partner Engagement</td>
<td>PIR motion sensors, contact sensors, actigraphy</td>
<td>Zarit Caregiver Burden scale – ZBI-12</td>
</tr>
</tbody>
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EVALUATE – AD: Dyad Analysis

J. Austin, 2016, unpublished
Thank you!

Harry Huskey (1916 – 2017)

kaye@ohsu.edu
Identifying Prodromal Markers:

The Everyday Cognition and Functional Activity Life Cycle
Behavioral Signature
(Geometric Interpretation)
Putting it all together: High dimensional data fusion model predicting analgesic class

66,172,380 observations

24/7 Behavioral - Activity Data: Computer use, time out of home, etc.

Weekly Self-Report: Mood, Pain, Falls, ER Visits, Visitors, etc...

Research Assessments: Cognition, Physical Function, Genetics, Biomarkers, etc.

Context: Weather, Consumer Confidence Index, etc.

Health Records: EHR, Pharmacy, Home Care, etc.

Outcome

Analgesic Class

Intervention

Austin et al. 2015
Predicting Drug Class Effects: Case of analgesics

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

<table>
<thead>
<tr>
<th></th>
<th>NSAID</th>
<th>Opioid</th>
<th>Both</th>
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<tbody>
<tr>
<td>Sensitivity (%)</td>
<td>94.9</td>
<td>65.9</td>
<td>67.4</td>
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<tr>
<td>Specificity (%)</td>
<td>99.9</td>
<td>98.6</td>
<td>99.6</td>
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<tr>
<td>Positive Predictive Value (%)</td>
<td>99.7</td>
<td>82.6</td>
<td>86.1</td>
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<tr>
<td>Negative Predictive Value (%)</td>
<td>99.7</td>
<td>96.6</td>
<td>98.9</td>
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<td>Correctly Classified (%)</td>
<td>99.6</td>
<td>95.6</td>
<td>98.6</td>
</tr>
</tbody>
</table>

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

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

n=95; Mean age 84 yrs