Continuous in-home assessment: New approaches to assessing health

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“This really is an innovative approach, but I’m afraid we can’t consider it. It’s never been done before.”
A fundamental limitation of current dementia research and clinical care... detecting meaningful change

Cardinal features of change - slow decline punctuated with acute, unpredictable events - are challenging to assess with current tools and methods.
Early detection

Detecting meaningful change is hard ... And how to improve detection of change

Symptoms Reported

Baseline 3 years 6 years

Is this the disease onset?

Functional range

Early detection
Changing the Assessment Paradigm

- New Observations & Discovery
- Maximally Effective Clinical Research & Trials
- Better Outcomes for Patients & Families

- Brief
- Episodic
- Clinic-based
- Subjective
- Obtrusive
- Inconvenient

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

- Pervasive Computing
- Wireless Technologies
- “Big Data Analytics”
Pervasive Computing Platform for Assessment: Community-wide ‘Life Lab’

Activity, Sleep, Mobility Time & Location

Balance, Body Composition
Heart Rate, Temperature, CO₂

MedTracker

Device/Sensor “X”

Secure Internet

Doors Opening/Closing

Phone Activity

Computer Activity

Research Process & Infrastructure

UNDERSTAND THE STAKEHOLDERS/KEY QUESTIONS
ROI (Response Over Internet) surveys, Focus Groups Participant/End-User Assessment

Secure Internet

UNDERSTAND REAL WORLD USE
Life Lab: Large Scale Deployments Relevant Health & Wellness Measures & Interventions in Everyday Environments

UNDERSTAND THE TECHNOLOGIES
Point of Care ‘Smart Apartment’ Lab: Focused Sensor/Measurement Technology Development & Assessment

UNDERSTAND THE DATA
ORCATECH Data Repository, Data Aggregation, Measurement Analytics & Outcomes
What can you see?

CDR = 0; MMSE = 28
CDR = 0.5; MMSE = 27
CDR = 0.5; MMSE = 28

ORCATECH
SENSING LIFE KINETICS

OREGON HEALTH & SCIENCE UNIVERSITY
Differentiation of early MCI: Total Activity & Walking

Activity patterns associated with mild cognitive impairment

Trajectories of walking speed over time

MCI cases 9X more likely in Slow Group
Differentiation of early MCI: Night-time Behavior & Sleep

• Adherence assessed continuously x 5 wks with MedTracker taking a
• Mean Age - 83 yrs
• Based on ADAScog: Lower Cognition Group vs Higher Cognition Group

Every Day Cognition: Computer use changes over time in MCI (assessing decline *without formal cognitive tests*)

- At Baseline: Mean 1.5 hours on computer/per day
- Over time:
  - Less use days per month
  - Less use time when in session
  - More variable in use pattern over time

Active, Frequent Assessments can be Delivered Everyday: RCT to Increase Social Interaction in MCI Using Home-based Technologies

- 6 week RCT of daily 30 min video chats
- 89% of all possible sessions completed; Exceptional adherence – *no drop-out*
- Intervention group improved on executive/fluency measure.
- MCI participants spoke 2985 words on average while cognitively intact spoke 2423 words during sessions; better discrimination of MCI than conventional tests (animal fluency and delayed list recall)

Direct to home visits: Novel assessment opportunities

Alzheimer’s Disease Cooperative Study
Home Based Assessment Study
(ORCATECH Kiosk System used in HBA Study)

http://psych.nyu.edu/freemanlab/research.htm
Putting it all together: Pervasive computing ‘Big Data’ for more informative research

LEGEND

Variety
Diverse
Certain
Uncertain

Veracity
(Circle Size)

B Biomarkers
C Clinical assessment
D Demographics
EB Everyday behavior monitoring
EF Environmental factors
EM Electronic medical record
G Genetics
P Population trends
S Self-report

Volume

Small Data Size
Large Data Size

Outcome of Interest

Predictive Model
Data Fusion/Aggregation

Austin, 2015
Putting it all together: High dimensional data fusion model predicting care transitions

63,745,978 observations

Context:
Weather, CCI, living in a retirement community, etc.

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

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

Annual Clinical Assessment:
Cognition, physical function, biomarkers, etc.

Demographics:
Age, education, socioeconomic status, etc.

Controls:
Number of rooms in home, etc.

Outcome
Care Transition

Austin et al. 2014 GSA
Predicting Care Transitions: Sensitivity Analysis

- Likelihood of a person transitioning within next six months – ROC AUC under curve = 0.974
Putting it all together: High dimensional data fusion model predicting drug (analgesic) class

Context:
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Annual Clinical Assessment:
Cognition, physical function, biomarkers, etc.

Demographics:
Age, education, socioeconomic status, etc.

Controls:
Number of rooms in home, etc.

Outcome
Analgesic Class

66,172,380 observations

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

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

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<th></th>
<th>NSAID</th>
<th>Opioid</th>
<th>Both</th>
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<tbody>
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<td>Sensitivity (%)</td>
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<tr>
<td>Specificity (%)</td>
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<td>Positive Predictive Value (%)</td>
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<td>Negative Predictive Value (%)</td>
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<td>Correctly Classified (%)</td>
<td>99.6</td>
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Logistic regression models treated as classifiers (and model fit statistics)
Pervasive Computing Technology in Current Therapeutics Research

• Spectacular progress has been made in applying technology to the basic biology of disease, creating an embarrassment of riches of potential treatments.

But...

• Pervasive computing technologies and selected biomarkers can radically change the way we conduct clinical research.
• This will lead to major advances in detecting prodromal change, managing manifest disease and in transforming the effectiveness of clinical trials.

appreciably changed since 1/47.
Harnessing the power of pervasive computing systems: *transform the conduct of clinical trials*
Challenges to detecting meaningful change in clinical trials

Dodge HH, et al. ADNI Biomarker progressions explain higher variability in stage-specific cognitive decline than baseline values in Alzheimer disease. Alzheimers Dement. 2014.
Improving clinical trials through continuous data collection: Smaller samples, more precise estimates, faster, and ecologically valid

Conventional Approach  
*Group Bell curves compared*

Continuously Monitored Approach  
*Individual Bell Curves*

Distribution can be generated for **EACH** individual within short duration data accrual periods

Walking Speed Observed During the First 90 days for 2 subjects

*Your walking speed ≠ my walking speed OR Your computer use ≠ my computer use*
Transforming Clinical Trials with High Frequency, Objective, Continuous Data: “Big Data” for Each Subject

- More precise estimates of the trajectory of change; allows for *intra-individual* predictions.
- Reduces required sample size and/or time to identify meaningful change.
- Reduces exposure to harm (fewer needed/ fewer exposed)
- Provides the opportunity to substantially improve efficiency and inform go/no-go decisions of trials.

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<th>MCI Prevention Trial – Sample Size Estimates</th>
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<td><strong>Current</strong></td>
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<tr>
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<td>SAMPLE SIZE TO SHOW 20% EFFECT</td>
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Dodge, et al. AAIC, 2014
Next Generation High Efficiency Clinical Trials (Focus on Phase II, early detection of efficacy)

Traditional Trial Enrichment:
Stratification according to increased risk of AD.
Does not predict who progresses

Biomarker Enrichment
Imaging, CSF, Plasma, Genetics, other risk factors

Further Enrichment:
Stratification according to who will progress.
Can predict who progresses

Behavioral Phenotype Enrichment
Sleep hygiene, Time out of home, etc...

Efficient Longitudinal Assessment:
Continuously assessed objective measures.
Detects individual relevant change rapidly

Continuous Assessment:
Computer use, Walking speed, Activity, Mobility, etc...

Population

AD Pathology Group

6 months

AD Pathology Group

2-3 months

Disease Progression Group(s)

Continuous Assessment: AD Progression

6 months
Thank You!

1956

2006

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