Delivering Health Coaching Interventions to the Home: Computational Models and Inference of Patient State

Holly Jimison, PhD, FACMI

Director

Consortium on Technology for Proactive Care

Northeastern University

- Funding
  - National Science Foundation
  - National Institute on Aging
  - National Institute on Nursing Research
  - Alzheimer's Association / Intel Company
  - National Institute on Standards & Technology
  - TEKES (Finland Government)
  - Halmstad University, Sweden
- No conflicts of interest
- Collaborative work with
  - Oregon Health & Science University
  - University of California at Berkeley

ORCATECH
SUCCESSFUL AGING WITH TECHNOLOGY

Polling question:
Who's in the audience?

Are you a:

- ❑ Clinician
- ❑ IT Expert
- ❑ Researcher
- ❑ Manager / Finance
- ❑ Other

(check all that apply)

Polling question:

How comfortable are you with math?

- ❑ Hate it
- ❑ Uncomfortable
- ❑ OK if needed
- ❑ Like it
- ❑ Bring it on

(check all that apply)

Monitoring->Care

GPS

EEG

Pulmonary Function

SpO_2

Posture

ECG

Gait

Blood Pressure

Balance

Step Height

Step Size

Training

Coaching

Chronic Care

Social Networks

Health Information

Performance

Prediction

Early Detection

Decision Support

Population Statistics Epidemiology Evidence

Inference

Datamining

M Pavel, H Watclar, CISE, NSF

Northeastern University

Polling question:

Do you monitor yourself at home?

- ❑ Activity (e.g., Fitbit)
- ❑ Sleep quality
- ❑ Weight
- ❑ Blood pressure
- ❑ Blood glucose

(check all that apply)

$200 iPhone case is an FDA approved ECG device

Ecological Momentary Assessment

Sorbi MJ, Mak SB, Houtveen JH, Kleiboer AM, van Doornen LJP
Mobile Web-Based Monitoring and Coaching: Feasibility in Chronic Migraine
J Med Internet Res 2007;9(5):e38
<URL: http://www.jmir.org/2007/5/e38/>

- Lifescan's OneTouch for blood glucose monitoring
- FDA approval
- Wirelessly syncs to iPhone / iPad
- 14 day summary
- Email or text sharing

Example: Medication Info

Sensors on Mobile Phones

- iPhones have
  - Noise sensor (microphone)
  - Proximity sensors
    - Detects face when using touchscreen; disable when putting phone to ear;
    - Acknowledging an alarm by waving your hand in front of the phone
    - Placing a phone into silent mode by turning it face down
    - Automatically turning speaker phone on by moving the phone away from your ear during a call
    - Automatically turning speaker phone off by moving the phone close to your ear during a call
  - Ambient light sensor
  - Accelerometers
  - GPS

- Related health coaching topics include sleep management, context awareness, etc.

Wirelessly Connect to Sensors

Other examples of sensors

- Nike FuelBand measures physical activity (time, calories, steps, model of total activity
- Fitbit has an accelerometer and an altimeter to track distance and stairs, infer sleep quality
- BodyMedia Link Armband measures physical activity level, calories, steps, heat flux, skin temperature, and galvanic skin response

Other examples of sensors

- Basis B1 Watch
  - Heart rate
  - Respiratory rate
  - 3D accelerometer
  - Body temperature
  - Ambient temperature
  - Galvanic skin response
- Apple watch
  - Heart rate
  - 3D accelerometer
  - Activity inference

Environmental sensor examples

- Mobile phone alerts and sensors outside the home (e.g., air quality)

New Environmental Sensors for Home Health Interventions

- Sensors to detect cigarette smoke in the home
  - Uses polymer films to collect and measure nicotine in the air (Eli Burakian, Dartmouth)
  - Ability to link to a smoking cessation coaching system

http://www.sciencedaily.com/releases/2013/03/130319144423.htm

Other examples of sensors

- Moticon makes an wireless sensor insole
- Weight distribution
- Motion

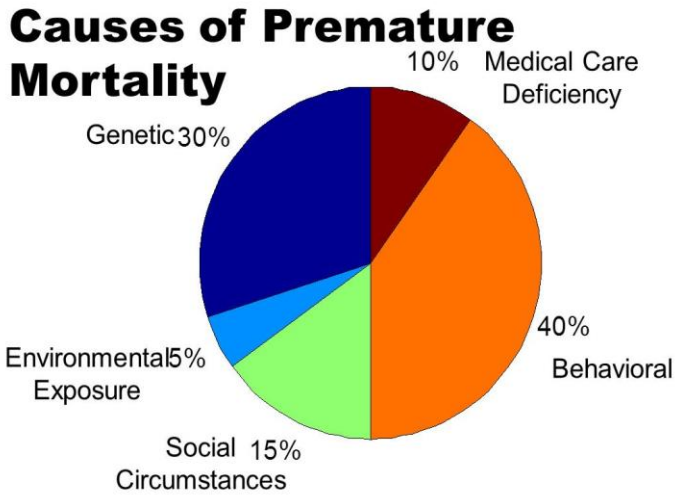
http://www.informationweek.com/mobile/10-wearable-health-tech-devices-to-watch/d/d-id/1107148?page_number=8

Others

- Imec makes a wearable EEG headset and ECG patch

Technology for Health Coaching

- Importance of health behavior change
- How technology can the scalability and effectiveness of hea interventions
  - Tailoring of materia.
  - Timeliness
  - Extend the reach of a coach



McGinnis JM, Russo PG, Knickman, JR. Health Affairs, April 2002.

Evidence-Based Principles for Coaching / Behavior Change

- Develop shared goals with patient preferences
- Assess readiness to change, motivations, triggers, barriers, self-efficacy
- Tailor interactions (action plan, messages)
- Continuous monitoring with just-in-time intervention

Examples from Monitoring Older Adults

- Examples of New Behavioral Measures (used in remote coaching research)
  - **Activity Monitoring in the Home**
  - **Cognitive Monitoring**
  - **Motor Speed**
  - **Sleep Monitoring**
  - **Socialization – Skype, phone, emails**
  - **Physical Exercise**
  - **Medication Management**
  - **Depression**

ORCATECH
SUCCESSFUL AGING WITH TECHNOLOGY

Northeastern University

Older Adult Participatory Design

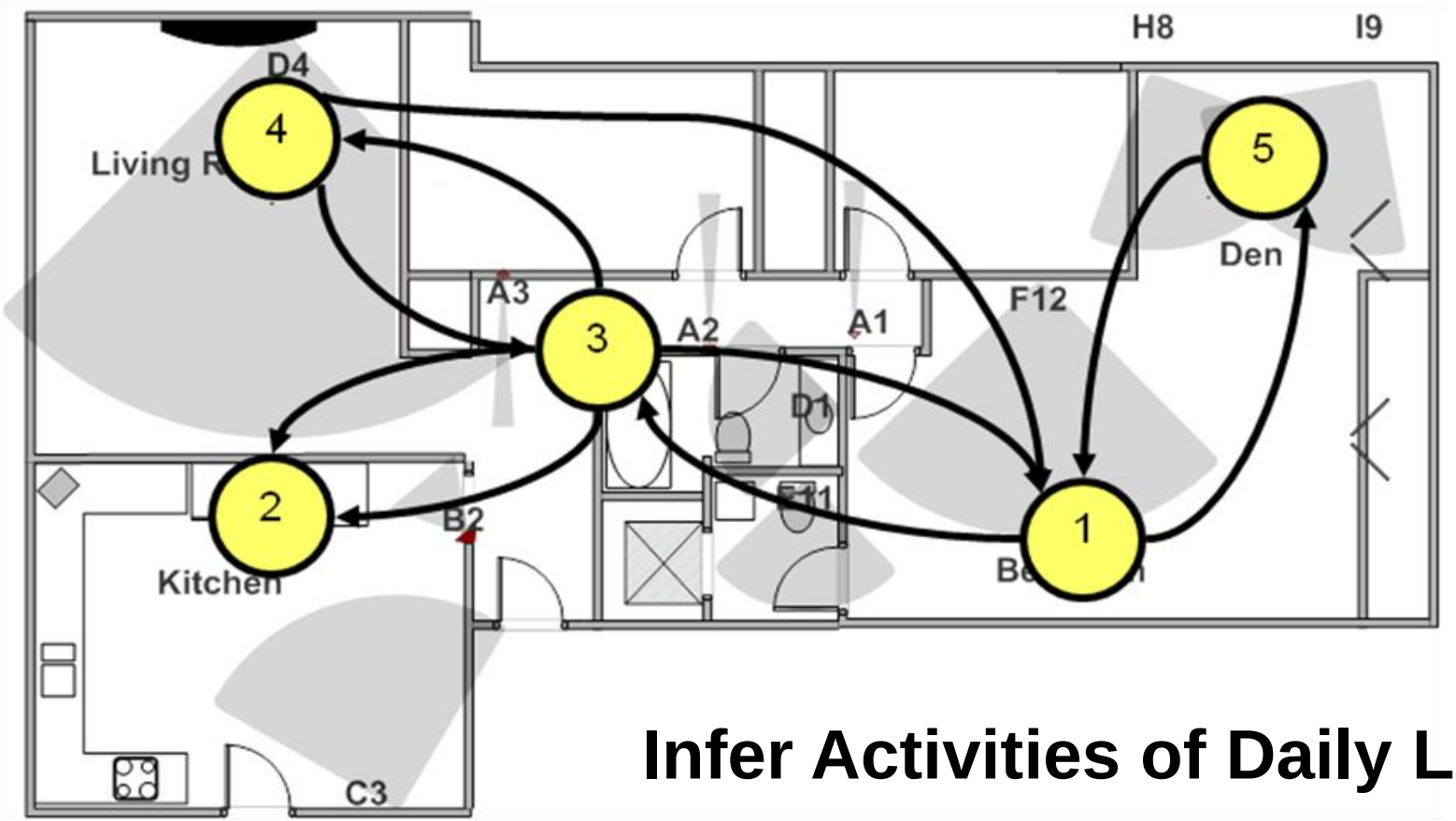
- Living Lab –
  - Community dwelling seniors
  - Portland area; now Boston
  - Living independently
  - Used to test technologies to support independent living and provide scalable quality care in the home setting

ORCATECH
SUCCESSFUL AGING WITH TECHNOLOGY

Northeastern University

Inference of Patient Activities Based on Sensor Data

Models to Infer Sensor Location & Legitimate Pathways



Infer Activities of Daily Living

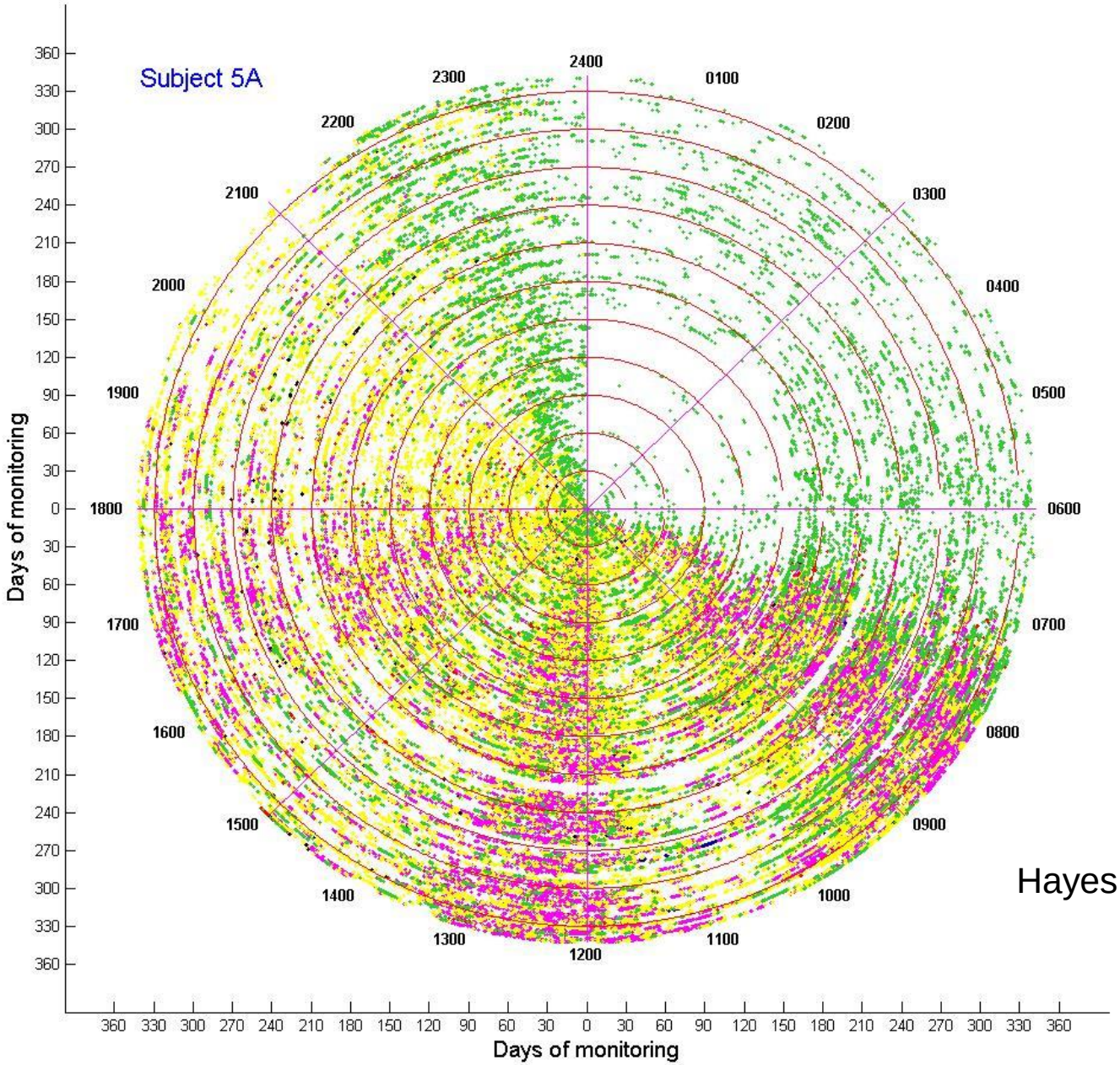
Pavel et al., The role of technology and engineering models in transforming healthcare, IEEE Reviews in Biomedical Engineering, 6:156-177, 2013.

ORCATECH
SUCCESSFUL AGING WITH TECHNOLOGY

Northeastern University

Activity Monitoring in the Home

Sensor Events
Private Home



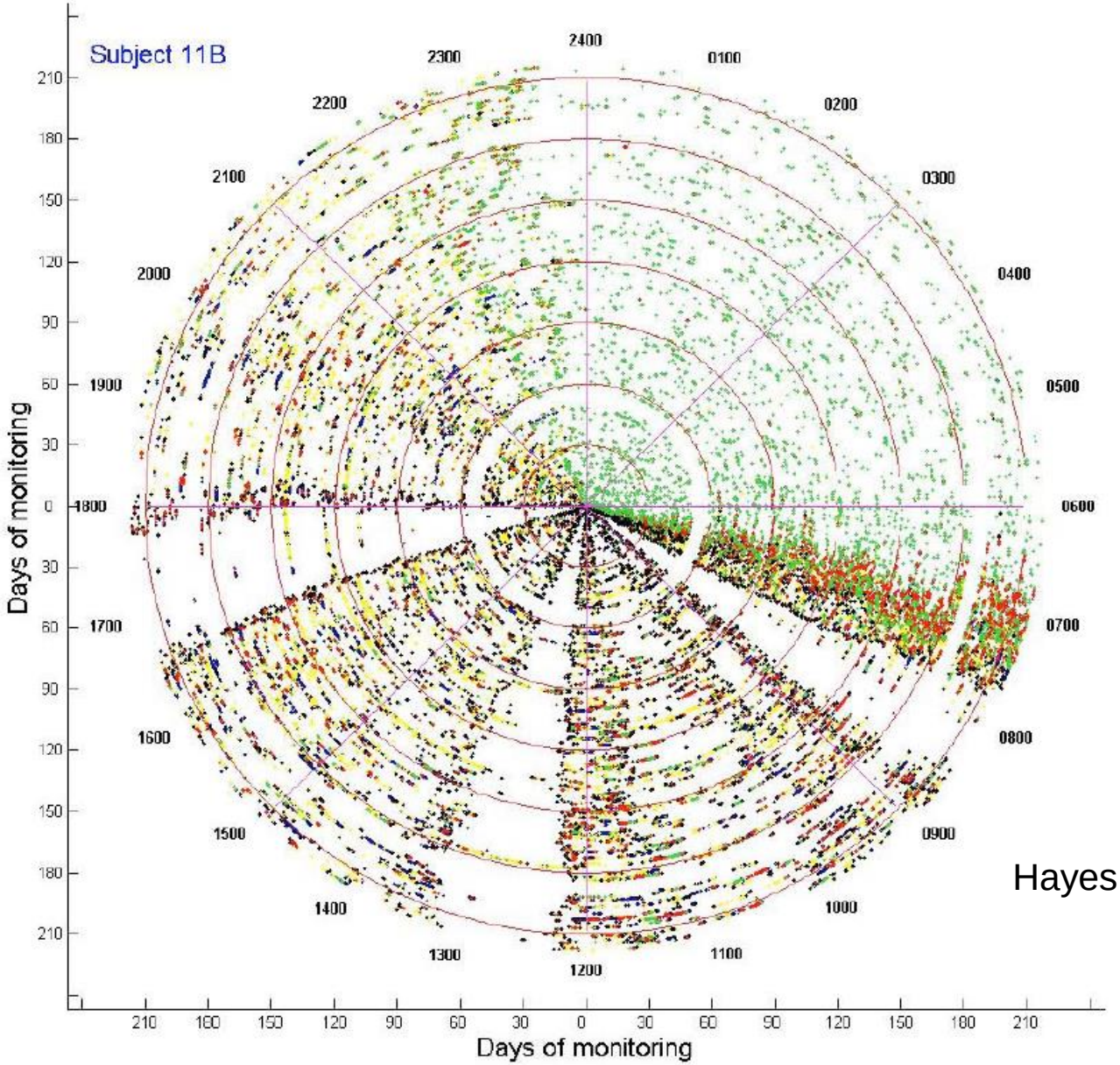
- Bedroom
- Bathroom
- Living Rm
- Front Door
- Kitchen

Hayes et al., www.orcatech.org

ORCATECH
SUCCESSFUL AGING WITH TECHNOLOGY

Activity Monitoring in the Home

Sensor Events Residential Facility



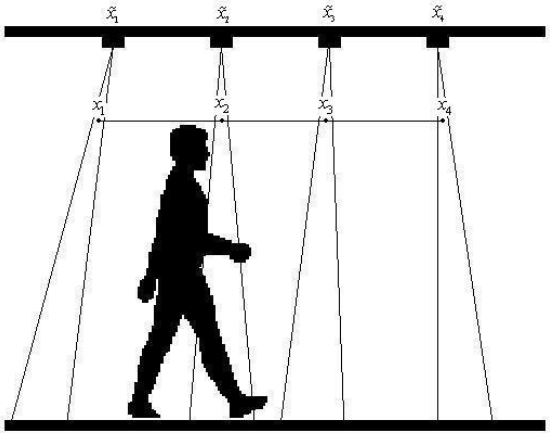
- Bedroom
- Bathroom
- Living Rm
- Front Door
- Kitchen

Hayes et al., www.orcatech.org

ORCATECH
SUCCESSFUL AGING WITH TECHNOLOGY

Measuring Gait in the Home

Unobtrusive gait measurement in-home with passive infrared (PIR) sensors

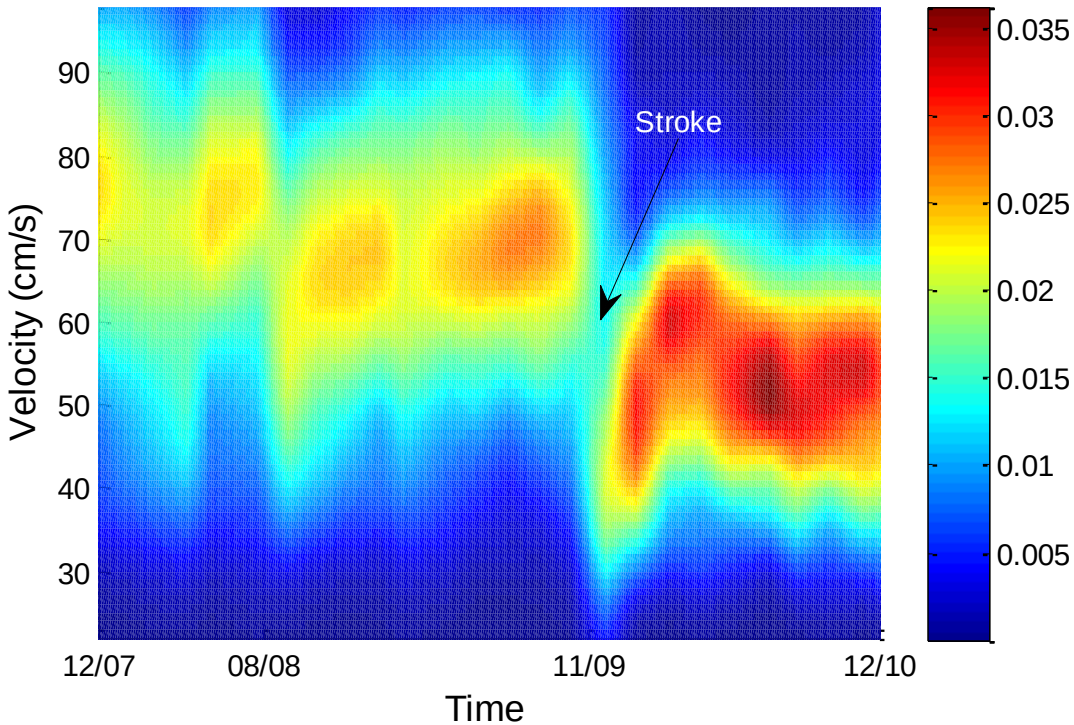


- Four restricted view PIR sensors
- Measure gait velocity whenever a subject passes through the “sensor-line”
- 200+ subjects monitored for > 4 years

Hagler et al., Unobtrusive and ubiquitous in-home monitoring: a methodology for continuous assessment of gait velocity in elders. IEEE Trans Biomed Eng, 57(4):813-20, *2010.*

ORCATECH
SUCCESSFUL AGING WITH TECHNOLOGY

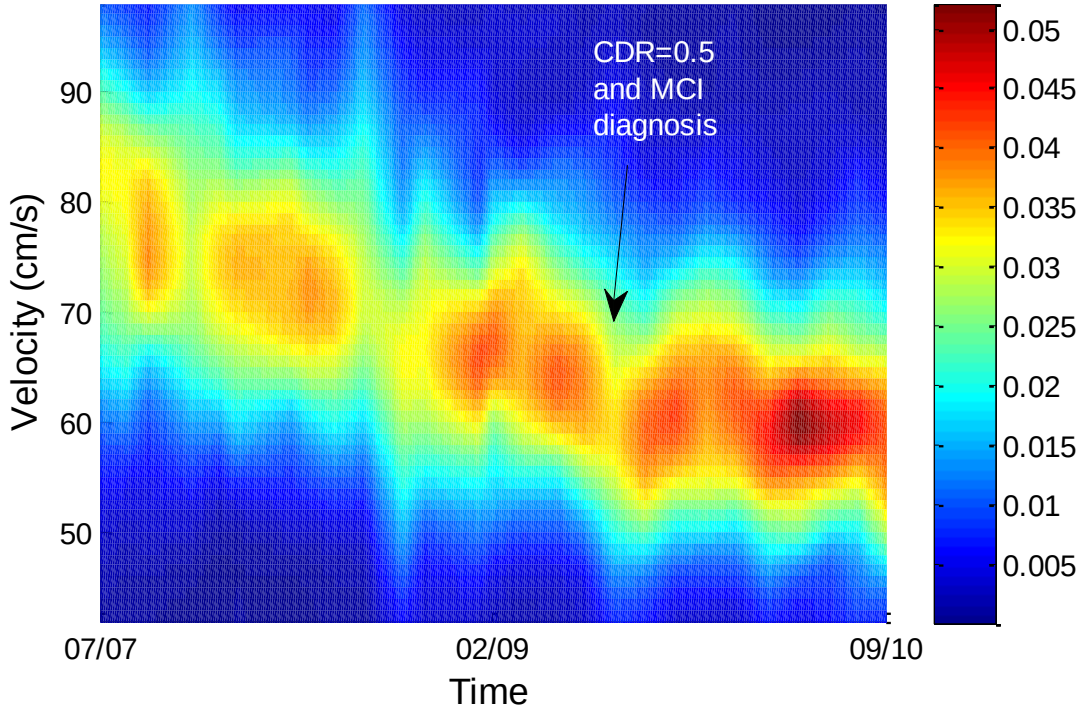
Subject 1



Austin D et al, Unobtrusive monitoring of the longitudinal evolution of in-home gait velocity data with applications to elder care. Conf Proc IEEE Eng Med Biol Soc., 2011.

ORCATECH
SUCCESSFUL AGING WITH TECHNOLOGY

Subject 2



Austin D et al, Unobtrusive monitoring of the longitudinal evolution of in-home gait velocity data with applications to elder care. Conf Proc IEEE Eng Med Biol Soc., 2011.

ORCATECH
SUCCESSFUL AGING WITH TECHNOLOGY

Creating Design Requirements for Coaching Technologies

- Focus groups with elders and caregivers
- Expert interviews with stakeholders
- Technology assessment and interoperability standards review
- Resulting design recommendations
  - Tailored action plans for health interventions
  - Home monitoring
  - Decision support
  - Integration of nurse care managers and family caregivers into the health care team
- Development of use cases

Jimison, HB and Pavel, M. Integrating Computer-Based Health Coaching into Elder Home Care, Technology and Aging, eds. Mihailidis, A., Boger, J., Kautz, H., and Normie, L., IOS Press, Amsterdam, The Netherlands, 2008.

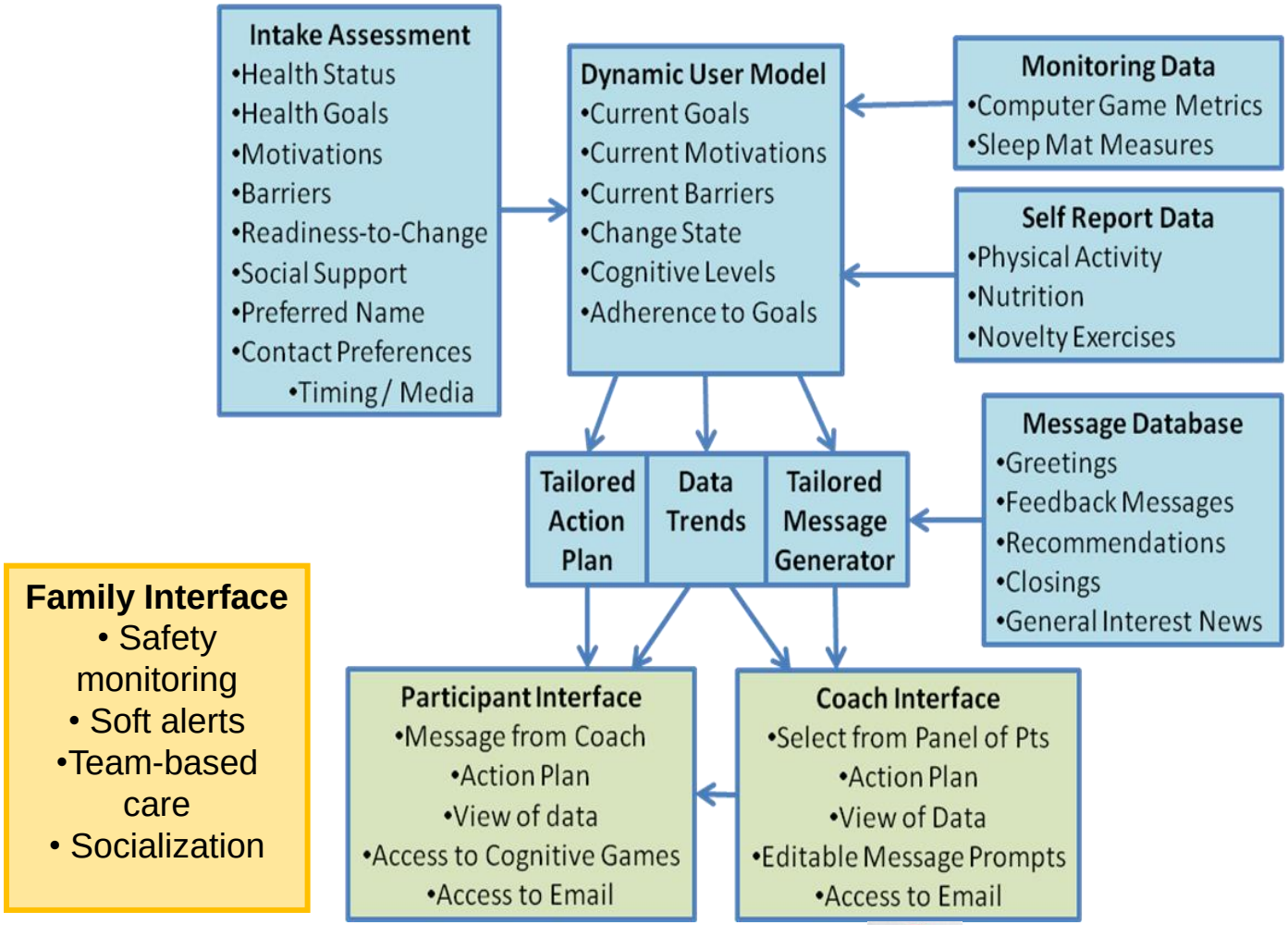
Cognitive Interventions to the Home

- Cognitive exercise, physical exercise, sleep management, etc. are a lifestyle interventions
- Remote, just-in-time, continuous care
- Incorporate principles of health behavior change
- Optimal use of lower cost personnel
- Integrate family & informal caregivers into the health care team (untapped resource)
- Platform for testing sustained cognitive interventions

Technology Approaches to Facilitating Health Coaching

- Effective use of resources
  - Wise use of face-to-face, Skype, phone interactions (build rapport, careful assessment)
  - Supplemented by automated or semi-automated messages
- Dynamic user model
  - Behavior change variables
  - Activity / context / health state estimates from sensor data

Dynamic User Model to Support Tailored Messaging



Northeastern University

Semi-Automated Messaging

Study of coaching efficiency with/without assisted messaging

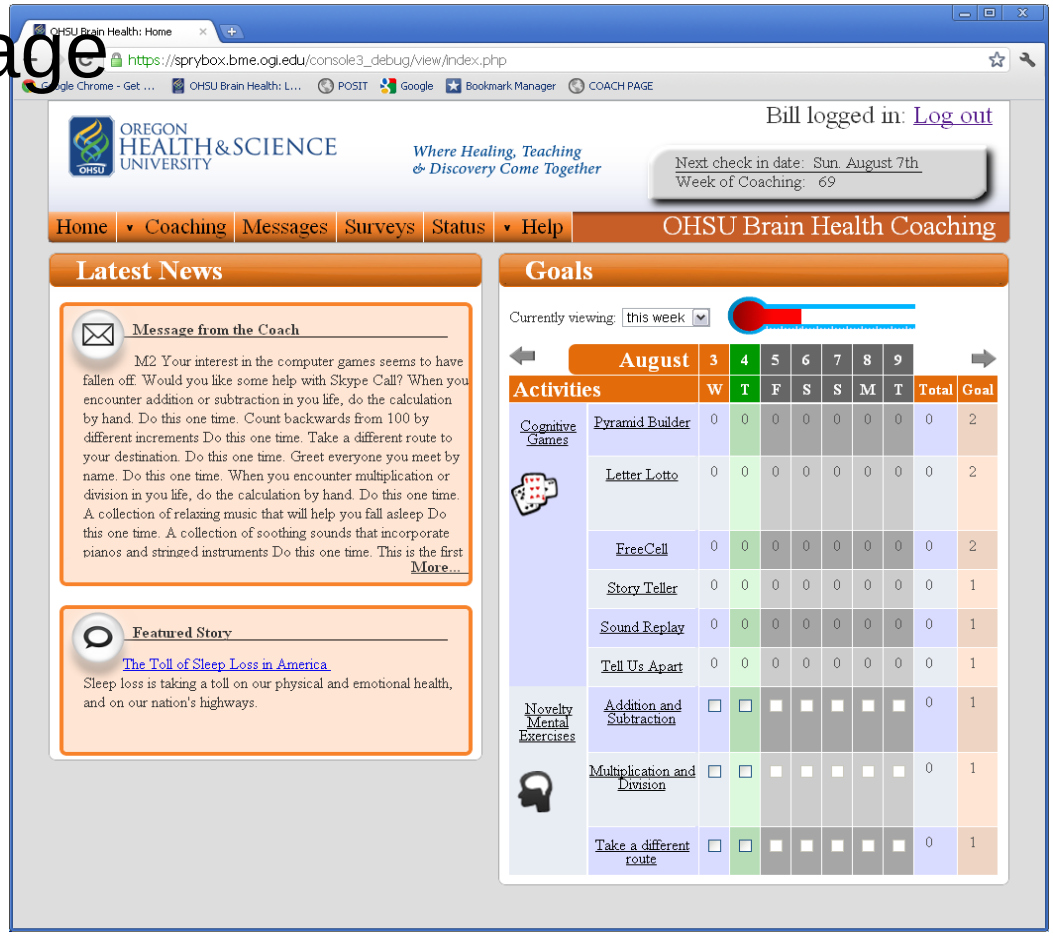
- Coaches (n=6) completed 4 coaching sessions for a panel of 10 (simulated) patients, half using automated system, half using manual system. Coaches were crossed over to alternate system after each session.
- **Efficiency** improved with semi-automated system (mean time to clear patient manual 4:26 min vs 2:39 min ($p<.04$)
- **Quality** of message judged equivalent on average by both patients and other coaches.

Michael Shapiro, MS Thesis, Oregon Health & Science University

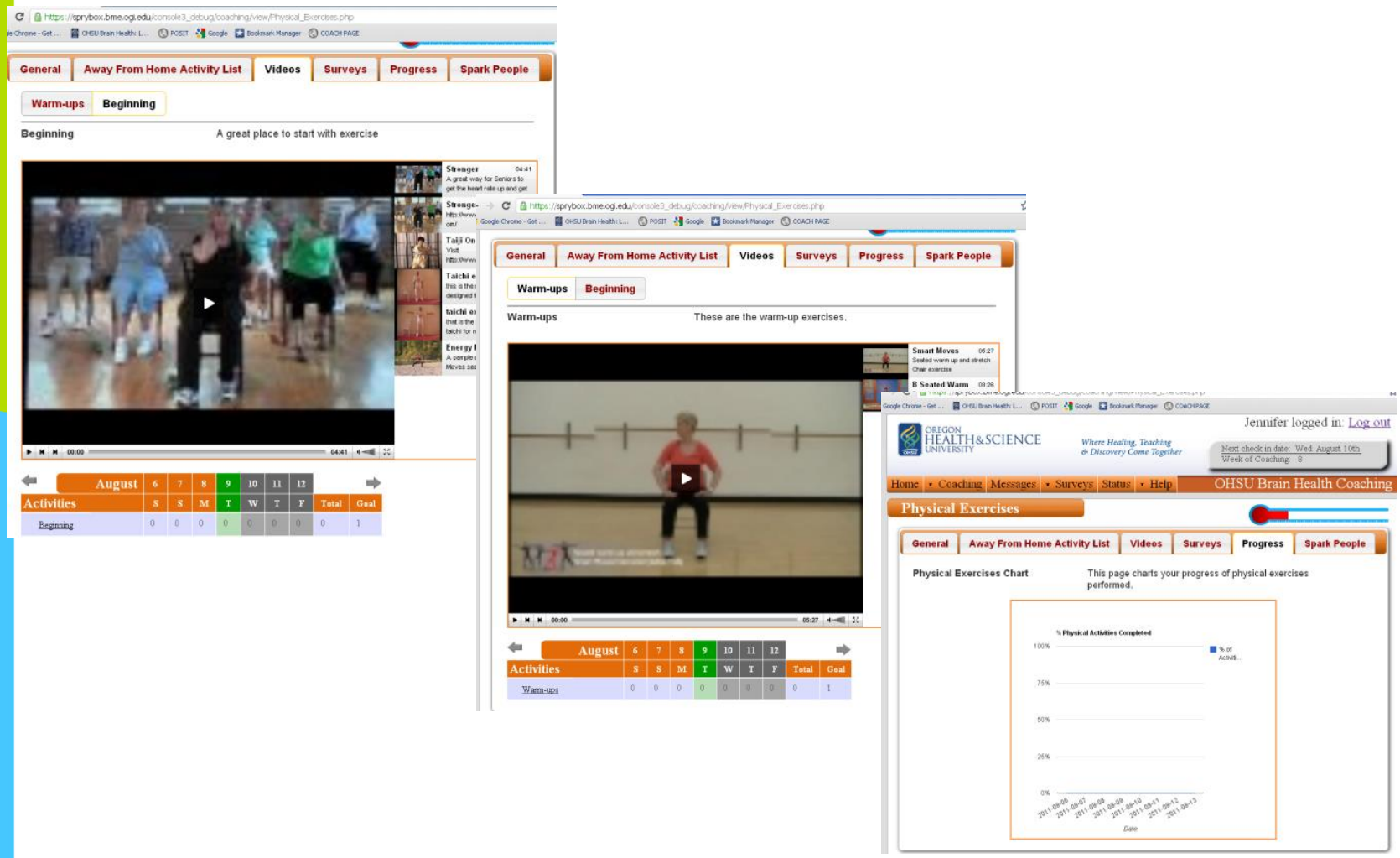
Participant Home Page

Participant home page

- Messages from coach
- Featured story
- Weekly goals
  - Activities
  - Surveys
- Access modules
  - Physical Activity
  - Sleep
  - Socialization
  - Novelty Mental Exercises
  - Cognitive Games
- Coaching Process
- Participant Materials



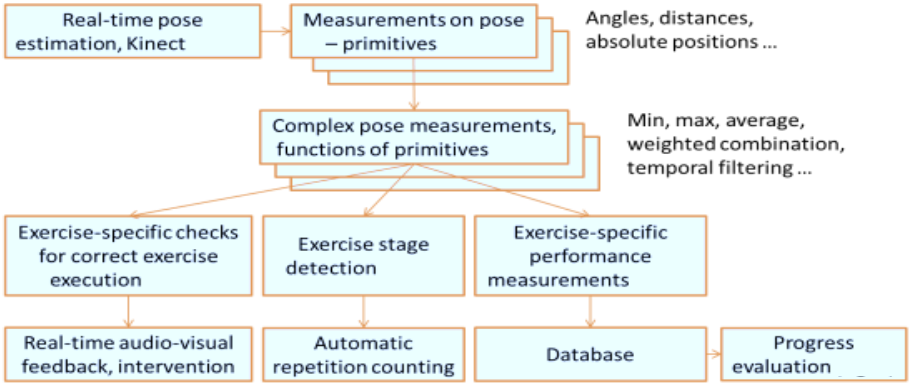
Physical Activity Module



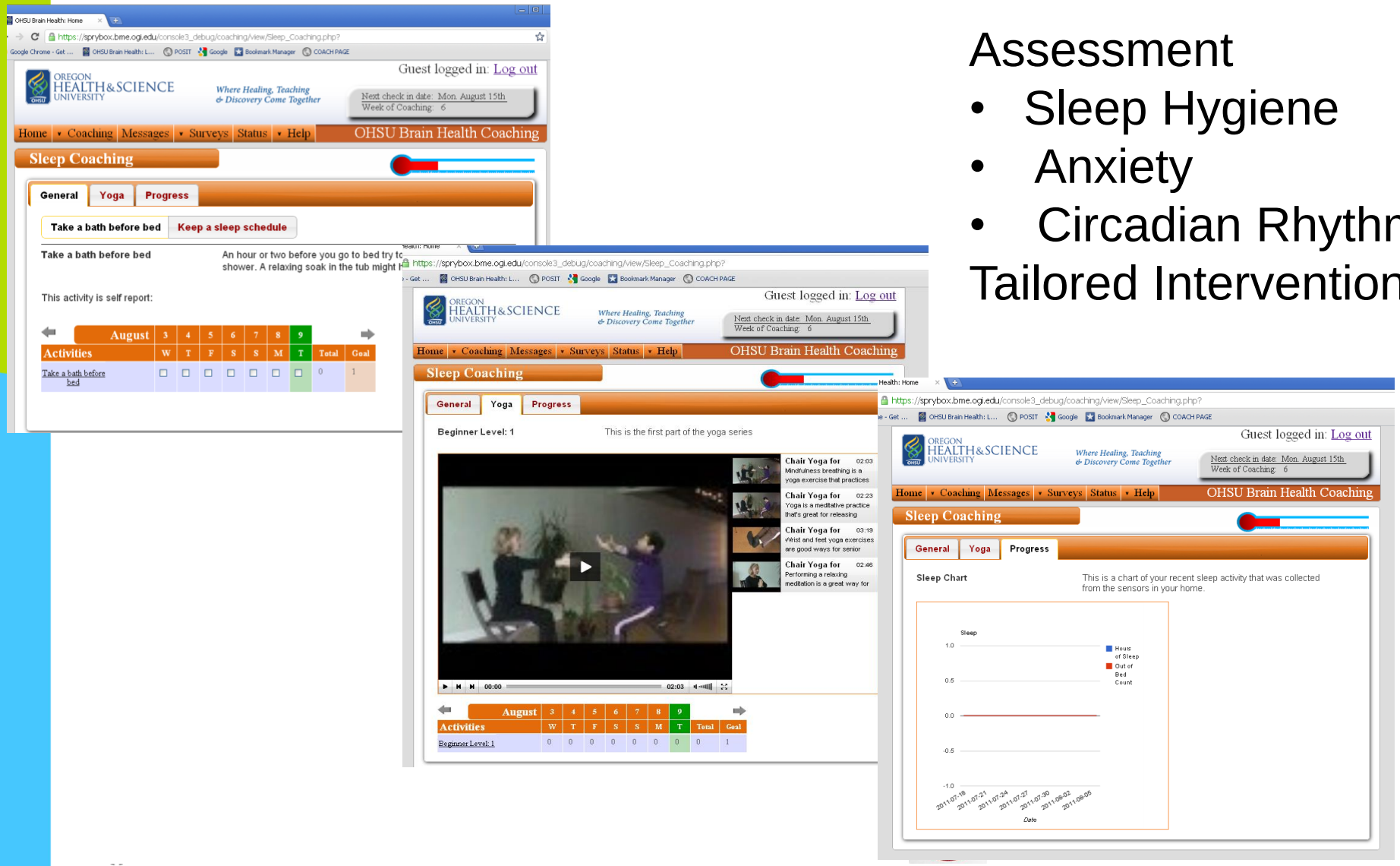
Northeastern University

Automated Coaching for Physical Exercise

- Collaboration with
  - Oregon Health and Science University
  - University California Berkeley
- Pre-recorded video clips for tailored exercise and Kinect Camera
- Real-time feedback based on image interpretation from Kinect skeleton representation
- Monitoring of balance, flexibility, strength, endurance
- Potential for remote interaction



Sleep Module



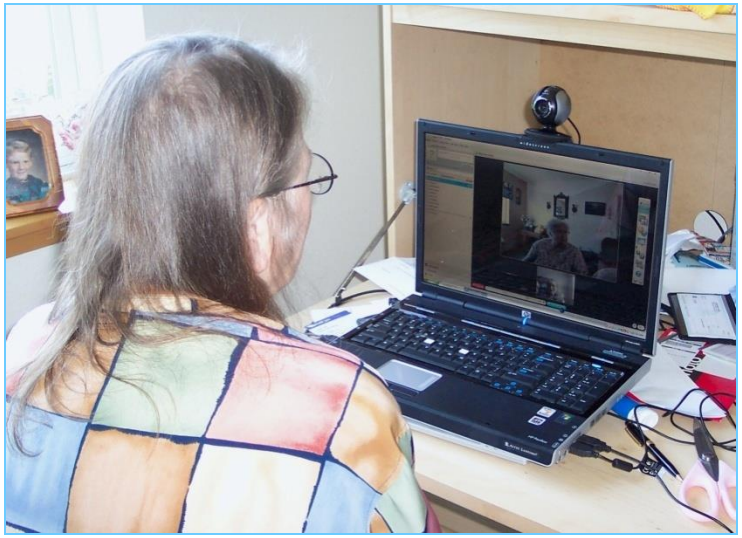
Assessment

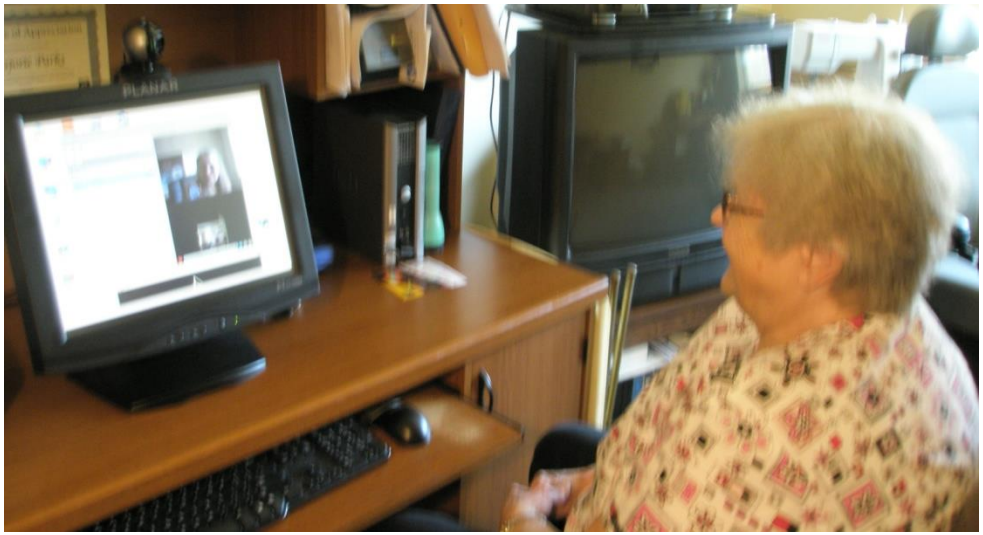
- Sleep Hygiene
- Anxiety
- Circadian Rhythm

Tailored Intervention

Socialization Intervention

- Web cams and Skype software given to participants and their remote family partner
- Frequent spontaneous use among participants

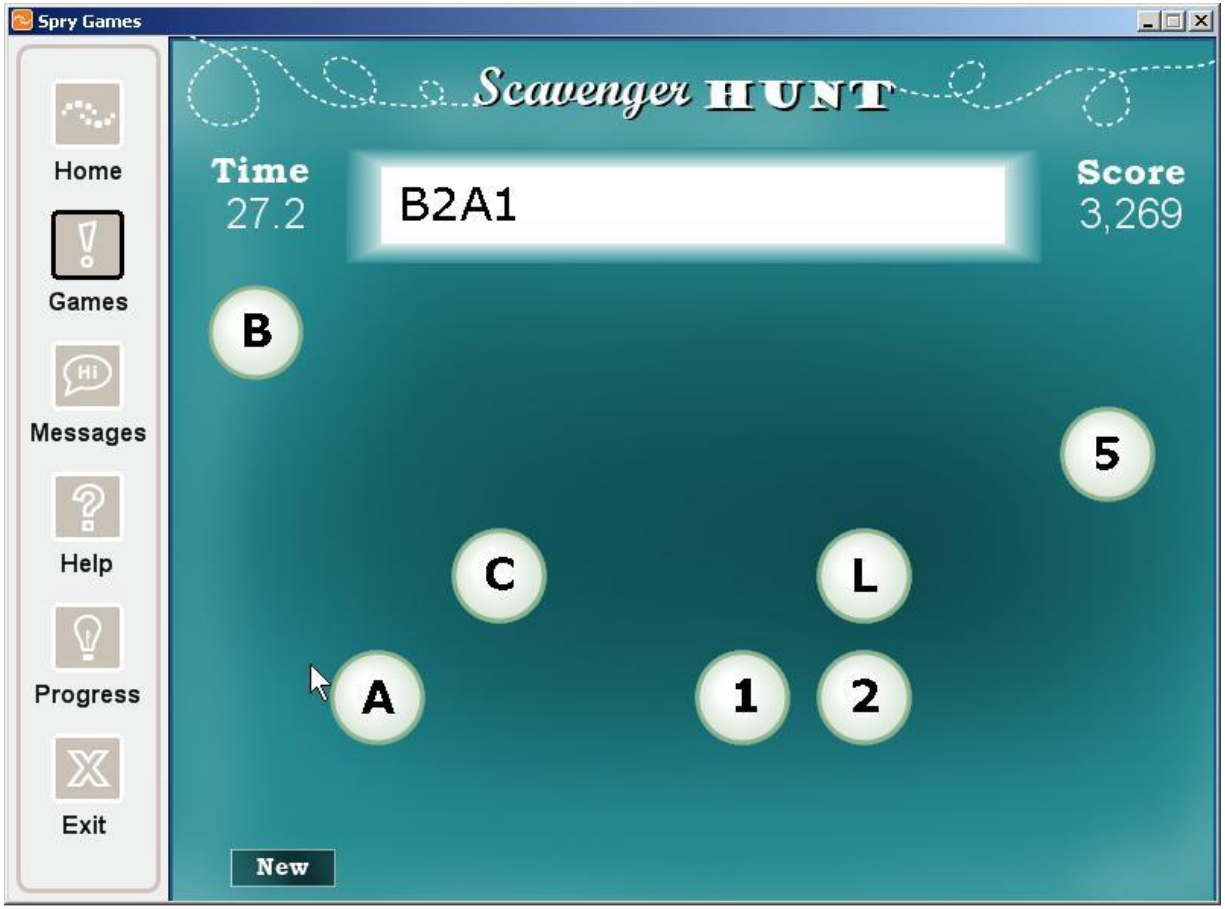




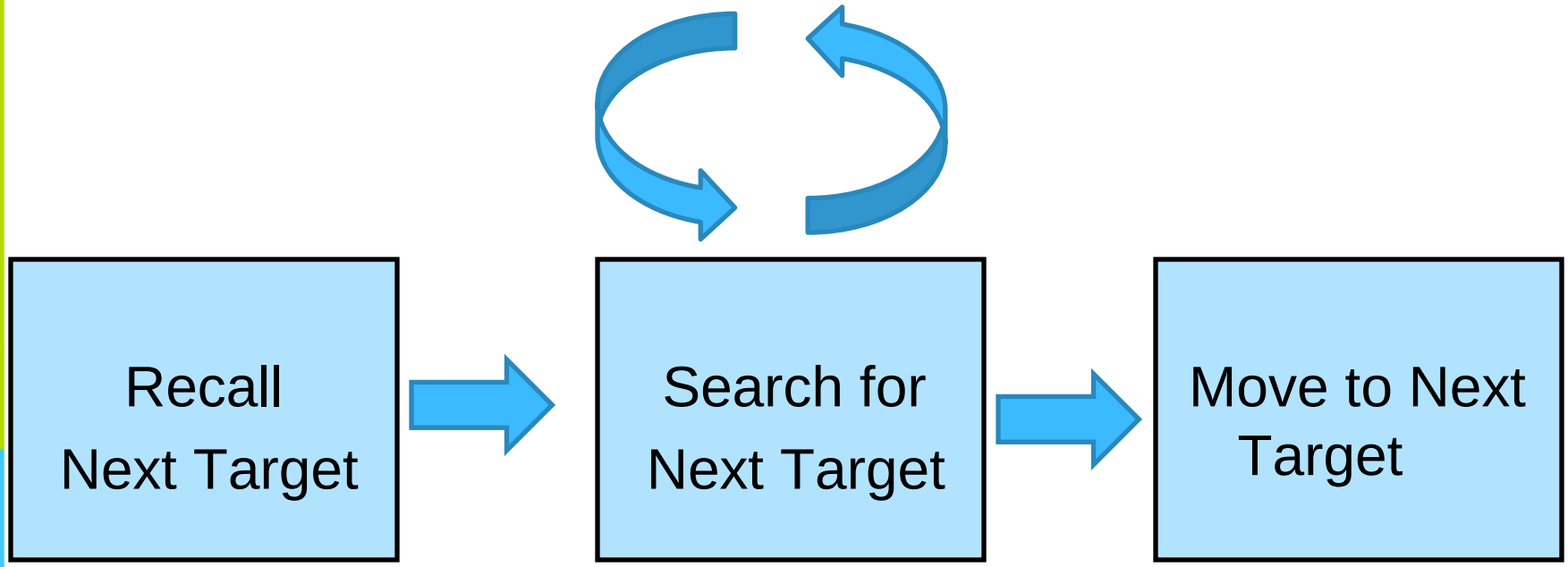
Cognitive Computer Games
(embedded cognitive metrics)

Northeastern University

Computer Game to Measure Executive Function



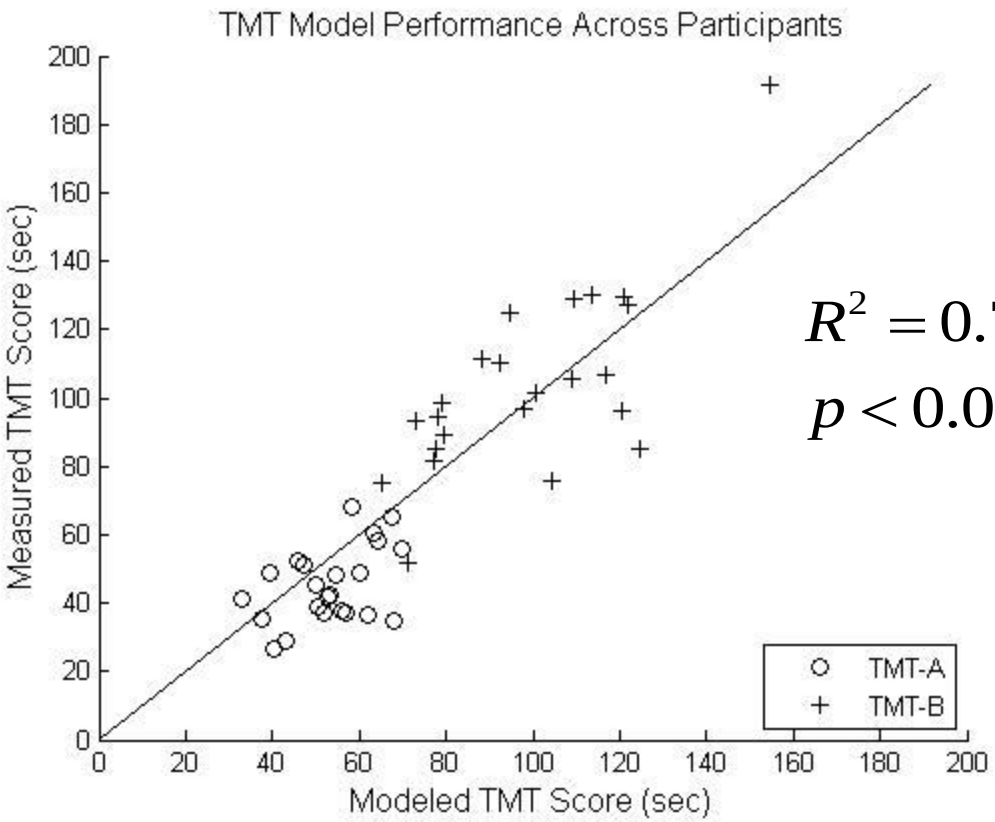
Model Recall, Search, Motor Speed



$$t_R + t_S(n,d) + t_M$$

S. Hagler, H. Jimison, M. Pavel, Modeling Cognitive Processes from Computer Interactions, IEEE Journal of Biomedical and Health Informatics, Vol 18, No, 4, 2014.

Predicting Neuropsych Test Scores



$$R^2 = 0.78$$

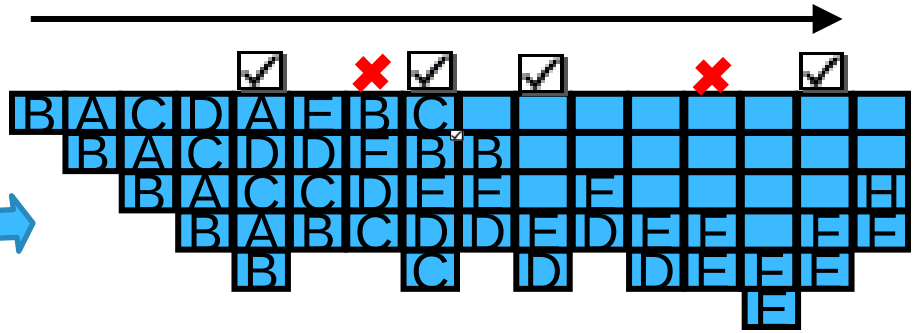
$$p < 0.0001$$

S. Hagler, H. Jimison, M. Pavel, Modeling Cognitive Processes from Computer Interactions, IEEE Journal of Biomedical and Health Informatics, Vol 18, No, 4, 2014.

ORCATECH
SUCCESSFUL AGING WITH TECHNOLOGY

Northeastern University

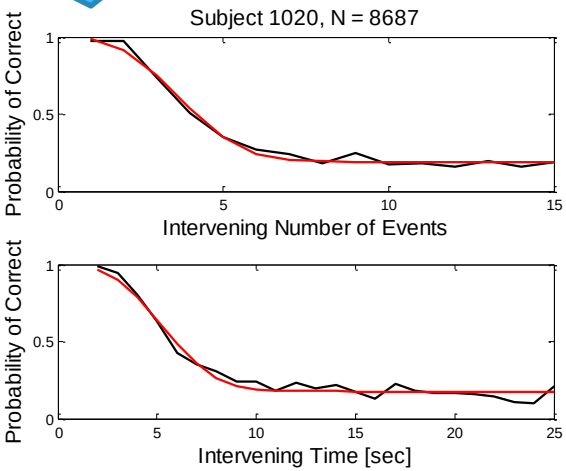
Cognitive Modeling Example: Memory



Characterize Memory Capacity

- Intervening number of events
- Intervening time
- Memory load

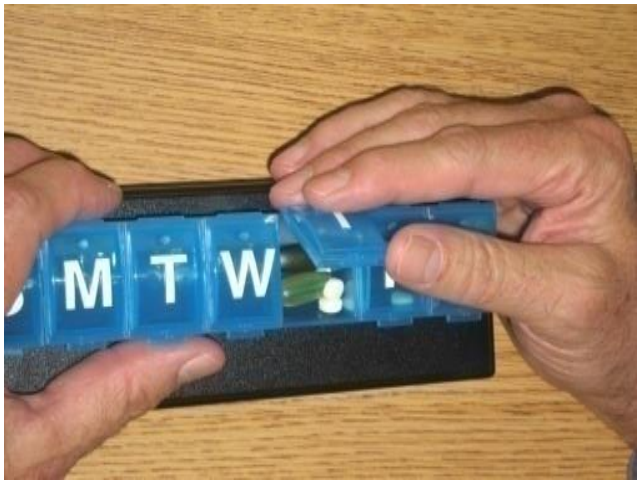
Simple Memory Model: Discrete Buffer



Characterize Memory Capacity with a Single Parameter

M Pavel, et al., www.ORCATECH.org

Medication Management



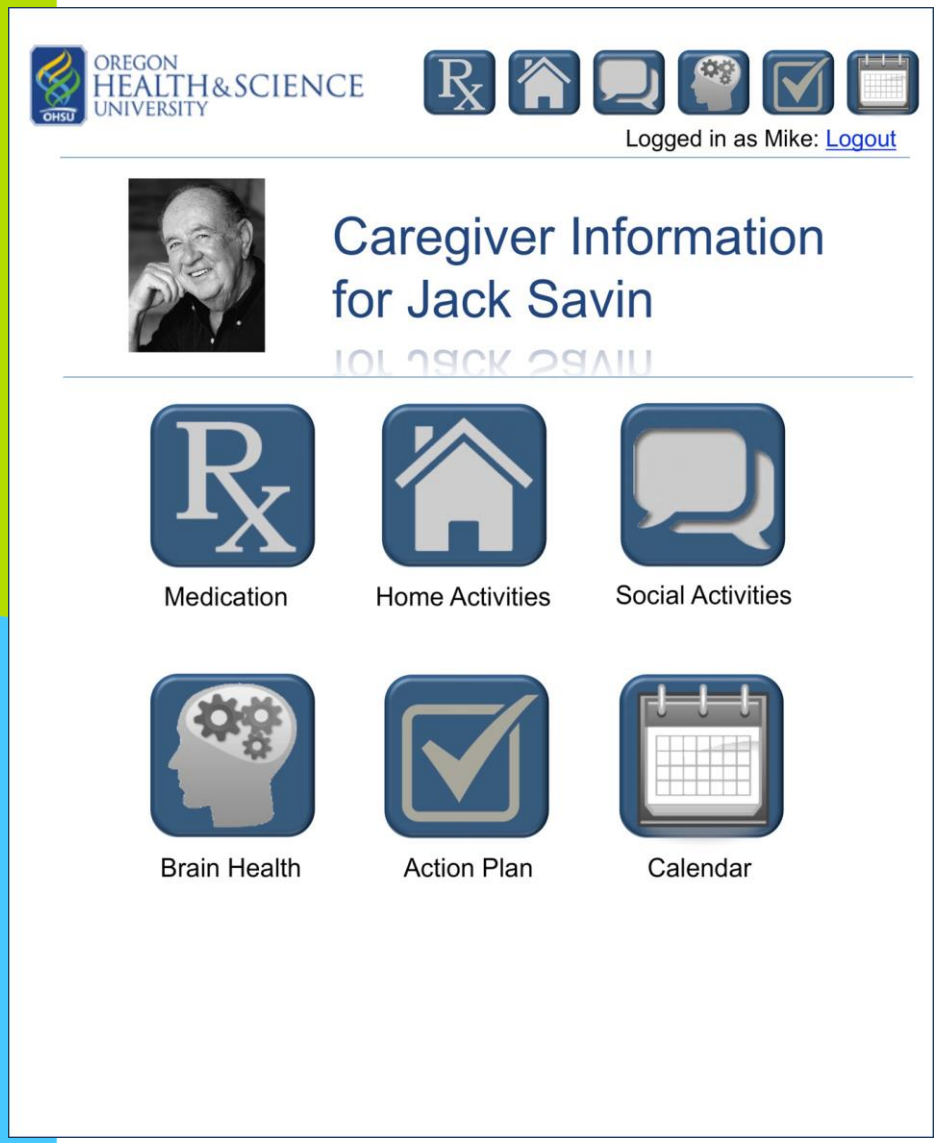
Bluetooth enabled dispenser

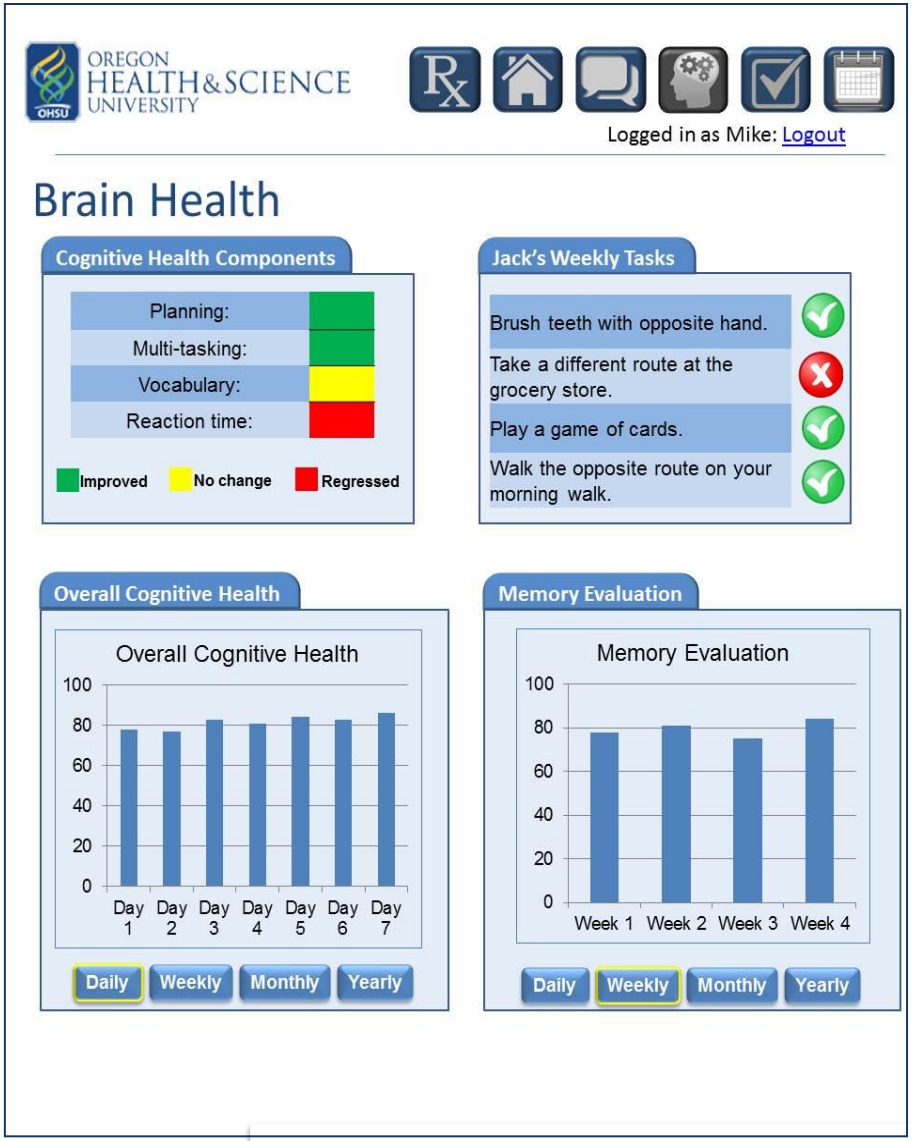
Web cam view underneath
Available to coach or remote family member

Interface options for:

- **Older adult**
- **Remote family member**
- **Community health worker**
- **Health coach**

Steven Williamson, PhD Dissertation,
Oregon Health & Science University





Steven Williamson, PhD Dissertation, Oregon Health & Science University

Polling question:

Concerns about being monitored?

- ❑ Yourself
- ❑ Your parents / grandparents
- ❑ Your patients

(check all that apply)

User reactions to tracking

- there is great variability in what factors about their life people would want to track
- what people wish to track will change over time, based upon their age, life circumstances, interactions with friends and family, health status, and general curiosity
- ubiquitous “monitoring” systems may be more readily adopted by end users if they are developed as tools for personalized, longitudinal self-investigation that primarily help end users, instead of or in addition to medical professionals, learn about the conditions and variables that impact their social, cognitive, and physical health.

Beaudin JS, Intille SS, Morris ME
To Track or Not to Track: User Reactions to Concepts in Longitudinal Health Monitoring
J Med Internet Res 2006;8(4):e29
<URL: http://www.jmir.org/2006/4/e29/>

Monitoring Attitudes from Older Adults

- Older adults are willing to trade privacy for increased independence and ability to age in place.
  - Adult children had more concern.
- Cognitive health was most important health concern (quality of life & independence).

- Jimison, HB and Pavel, M. Integrating Computer-Based Health Coaching into Elder Home Care, Technology and Aging, eds. Mihailidis, A., Boger, J., Kautz, H., and Normie, L., IOS Press, Amsterdam, The Netherlands, 2008.

Privacy Implications

- Need for modeling preferences for data sharing
  - Coach or community health worker
  - Various clinicians
  - Family members
  - Neighbors, etc.
- Further work on the appropriate level of summarization for each member of the care team

Lessons Learned

- Algorithm Issues
  - New analytic models for developing behavioral markers derived from sensor data
  - Dynamic user models
  - Tailored message generation
  - Privacy / Security – tailored data sharing
  - User centered design – ease of use
- Protocol Issues
  - Need to have a variety of activities for novelty and sustained engagement
  - Coaching (automated and in-person) important

Summary:
Considerations when Designing eHealth Behavior Change Interventions

- Make use of sensors and data analytic models
- Remote, just-in-time, continuous care
- Integrate principles of health behavior change
- Usability
- Access issues, culture, literacy, etc.
- Integrate family & informal caregivers into the health care team (untapped resource)
- Security & privacy issues
- Business model

Polling question:

Is there a VA business model for :

- ❑ Medication mgt
- ❑ Sleep mgt
- ❑ Physical Ex
- ❑ Stress/Depr mgt
- ❑ Socialization

(check all that apply)

Acknowledgements

Collaborations:

- Northeastern University: Holly Jimison, Misha Pavel, Christine Gordon, Stuart Hagler, Xuan Li
- Oregon Health & Science University: Paul Gorman, Jennifer Marcoe, Nicole Larimer, Jon Yeargers, Steve Williamson, Don Young
- UC Berkeley: Ruzena Bajcsy, Gregorij Kurillo, Ferda Olfi
- Tampere University of Technology / VTT: Ilkka Korhonen, Niilo Saranummi, Jose Perez-Macias, Elena Helander, Anita Honka, Julia Pietila
- Halmstad University: Ingela Skärsäter, Kristina Ziegert, Anita Sant'Anna, Nicholas Wickström

Funding:

- National Institute on Nursing Research (P20-NR015320)
- National Science Foundation (grants 1407928 and 1111965)
- National Institute on Aging (P30AG024978 and ASMMI0116ST)
- Alzheimer's Association / Intel Company
- National Institute on Standards & Technology
- TEKES (Finland Government)
- Halmstad University, Sweden

Northeastern University

Questions?

Contact:

Holly Jimison, PhD, FACMI
h.jimison@neu.edu

Consortium on Technology for Proactive Care
Northeastern University