Big Data Challenges in Delivering Health Coaching Interventions to the Home

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Consortium on Technology for Proactive Care

College of Computer & Information Science

&

School of Nursing

Northeastern University

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

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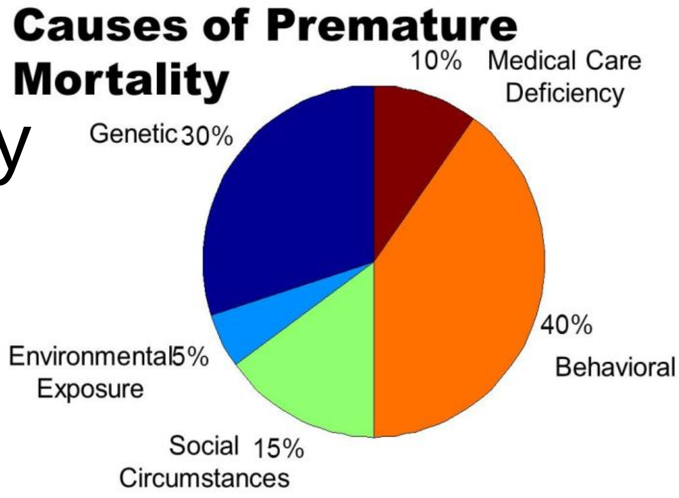
Technology for Health Coaching

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



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

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Evidence-Based Principles

Theory-based coaching

- 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

Current practice

- ✓ Human - phone interaction at baseline
- ✓ Human - phone interaction at baseline
- ✓ Human phone interaction at baseline
- -- Predetermined set intervals for phone calls

What do coaches actually do?

Motivational Interviewing

- Collaborative (don’t impose)
- Assess motivations to change
- Assess barriers to change
  - What are the triggers?
  - Develop problem solving plan for dealing with those situations
- Develop a tailored shared action plan
- Monitor & provide feedback / encouragement

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**

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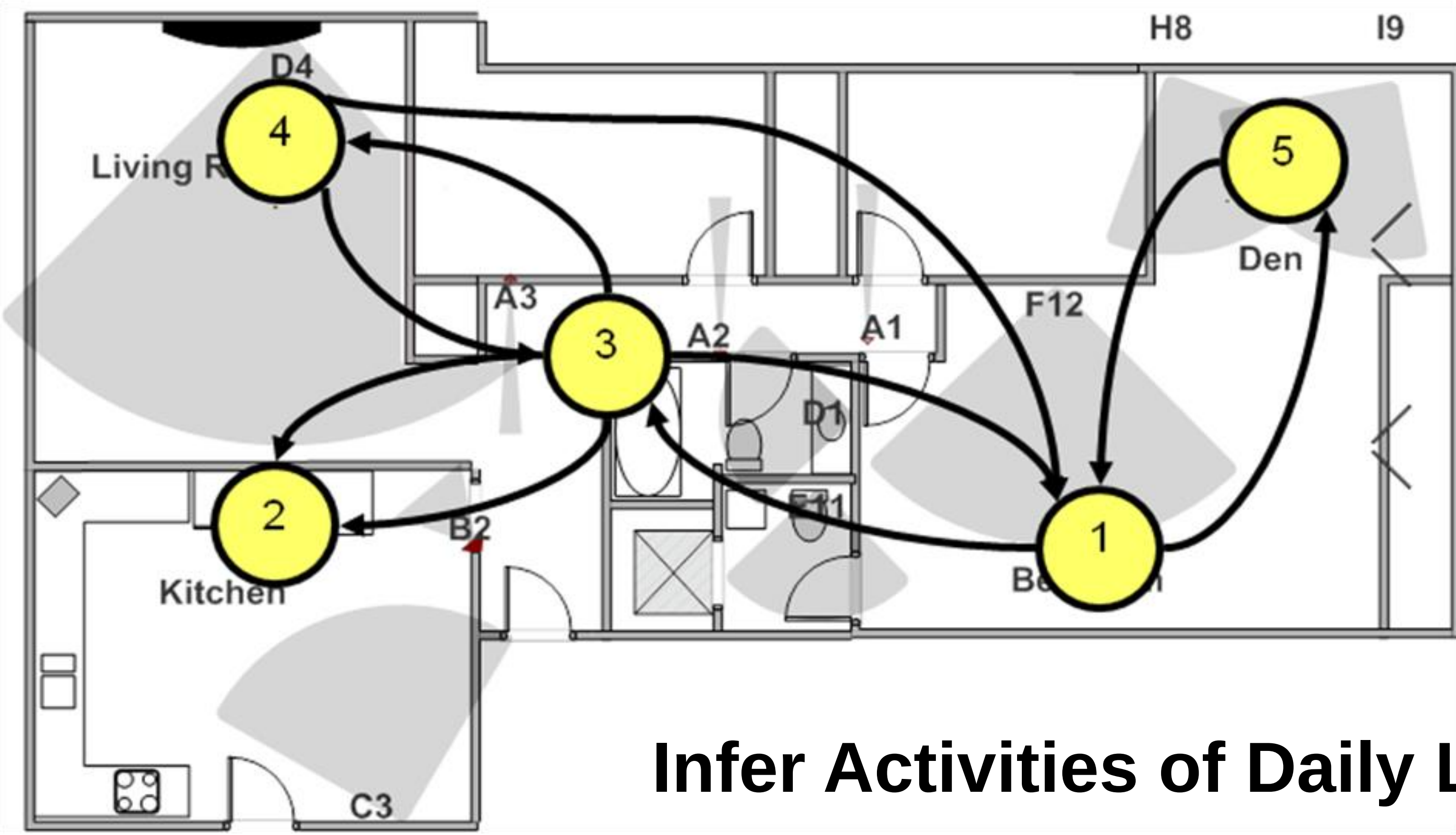
Inference of Patient Activities Based on Sensor Data

Models to Infer Sensor Location & Legitimate Pathways

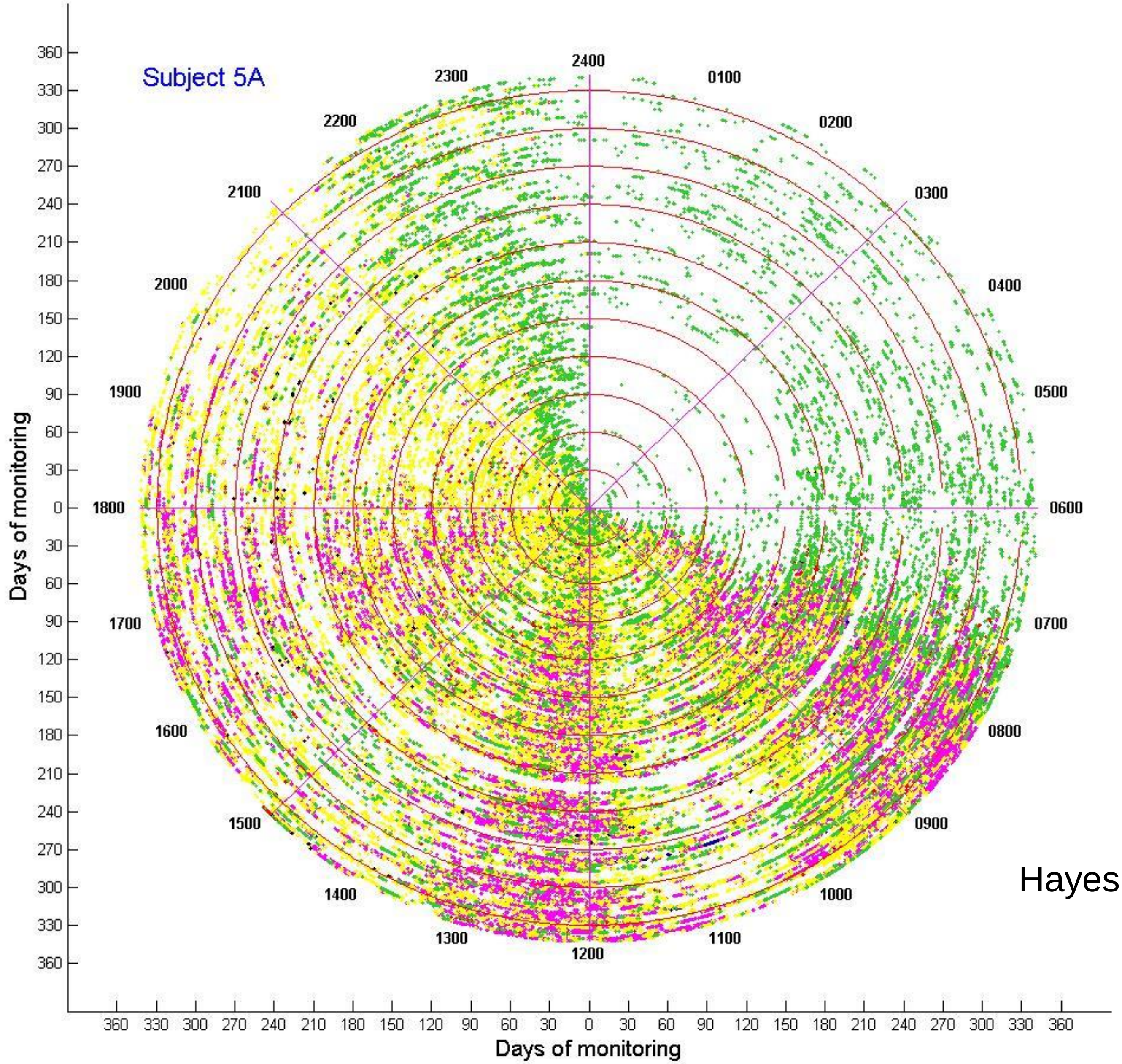


Infer Activities of Daily Living

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

Activity Monitoring in the Home

Sensor Events
Private Home



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

Hayes et al., www.orcatech.org

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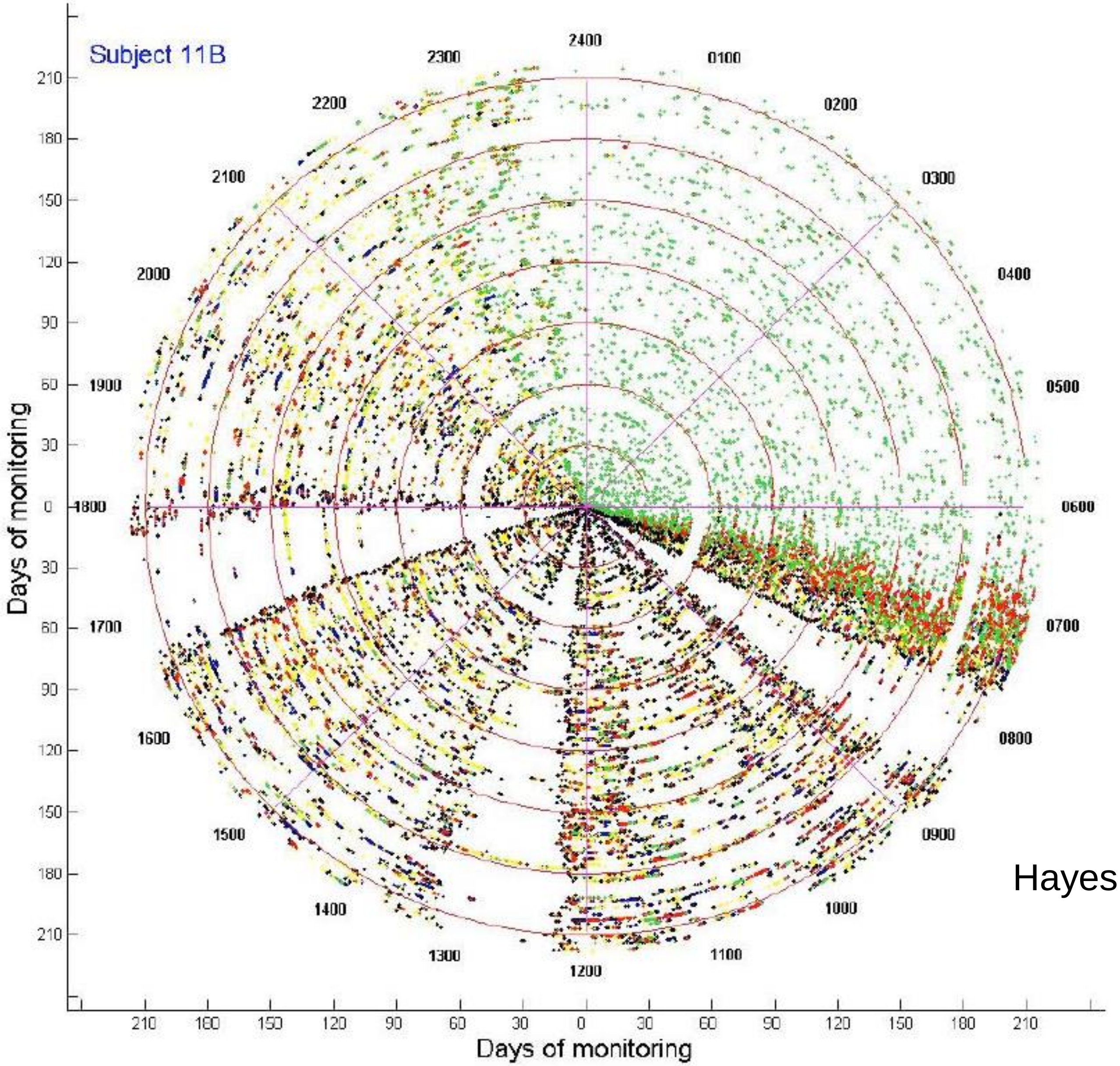
Activity Monitoring in the Home

Sensor Events Residential Facility

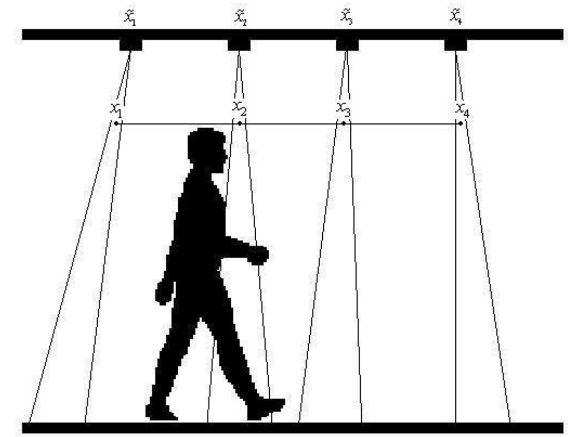


- Bedroom
- Bathroom
- Living Rm
- Front Door
- Kitchen

Hayes et al., www.orcatech.org

Measuring Gait in the Home

- Unobtrusive gait measurement in-home with passive infrared (PIR) sensors *- Hagler, et al., IEEE Trans Biomed Eng, 2010*
  - Four restricted view PIR sensors
  - Measure gait velocity whene
  - subjects passes through th
  - “sensor-line”
  - Deployed for the Intelligent
  - Systems for Assessing
  - Aging Changes (ISAAC) study
  - 200+ subjects monitored for > 4 years



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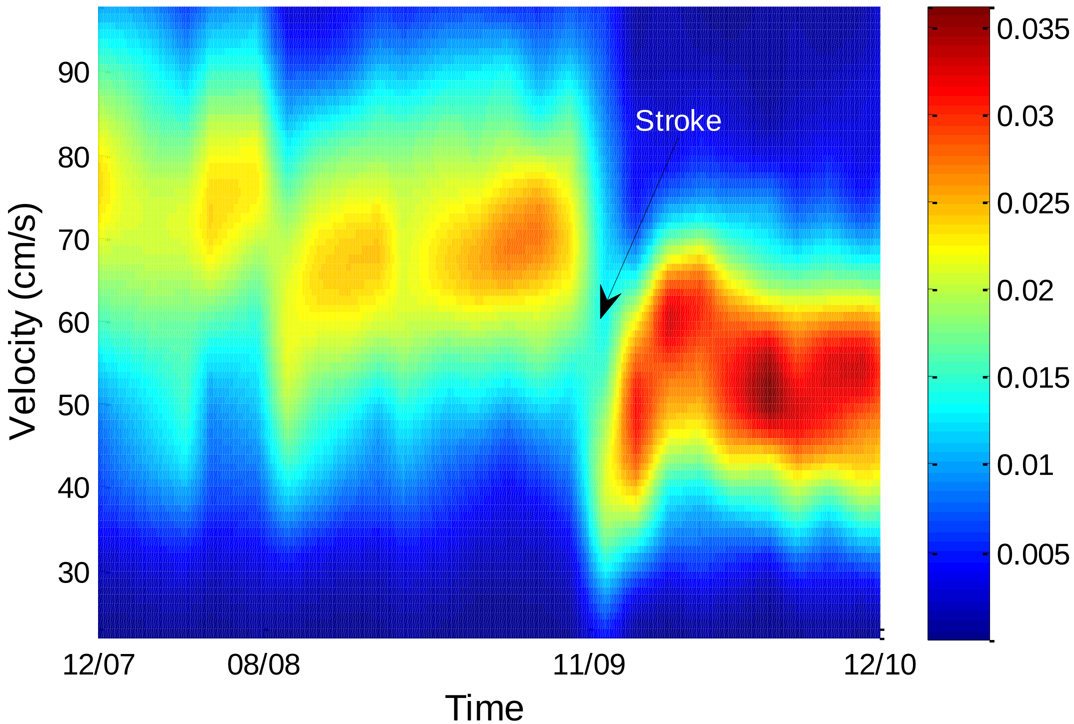
Subject 1



Austin et al, Sept 2011 - EMBC (Gait)

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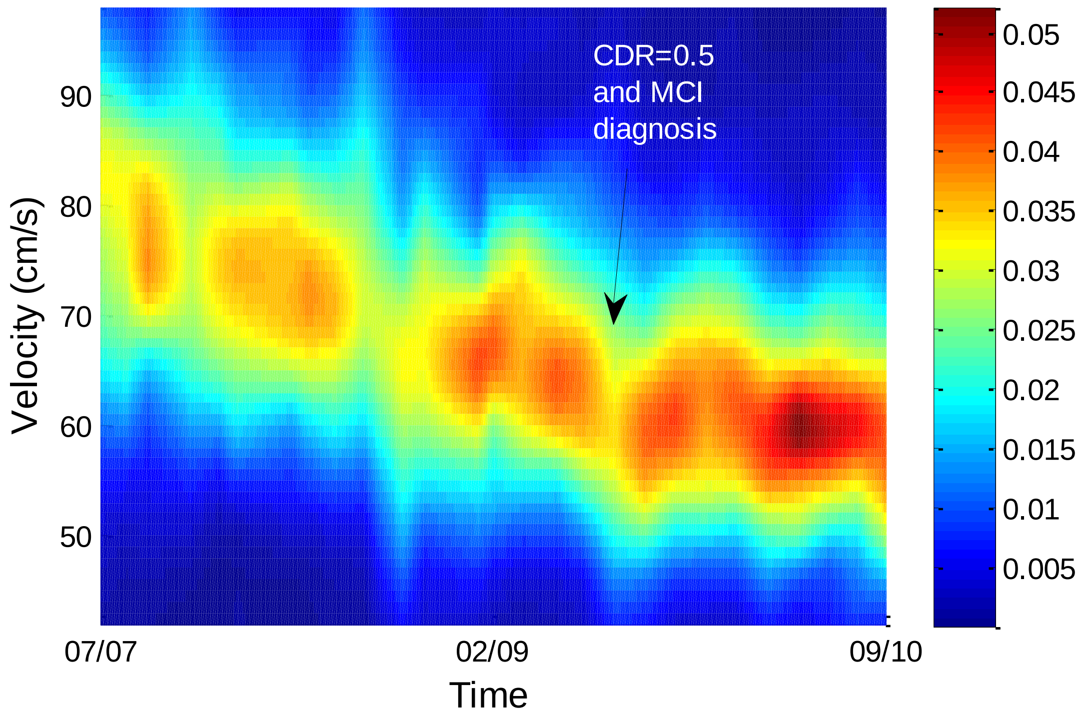
Subject 2



Austin et al, Sept 2011 - EMBC (Gait)

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Creating Design Requirements

- 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.

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

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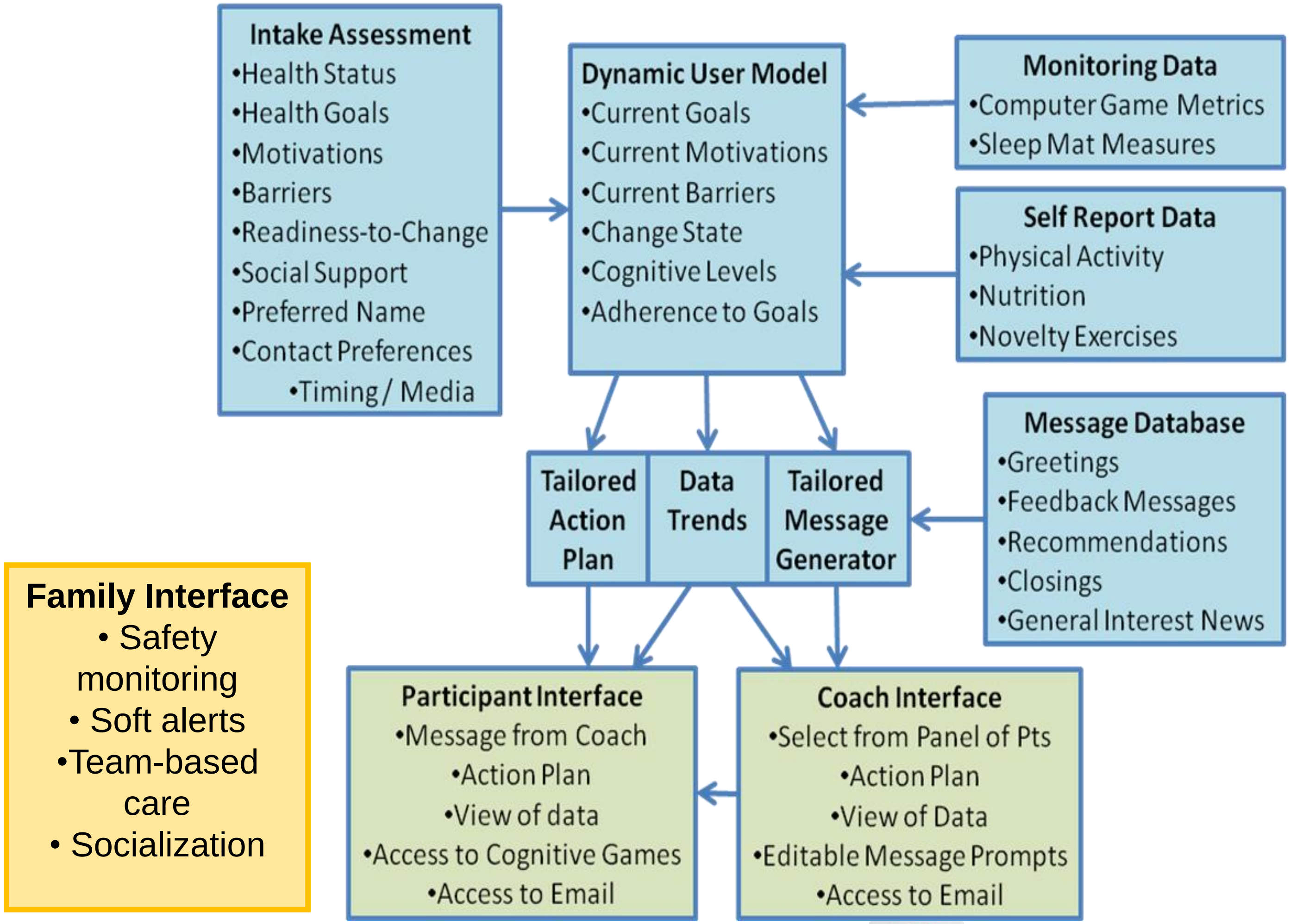
Technology Approaches to Facilitating Health Coaching

- 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



Semi-Automated Messaging

Study of coaching efficiency with/without assisted messaging

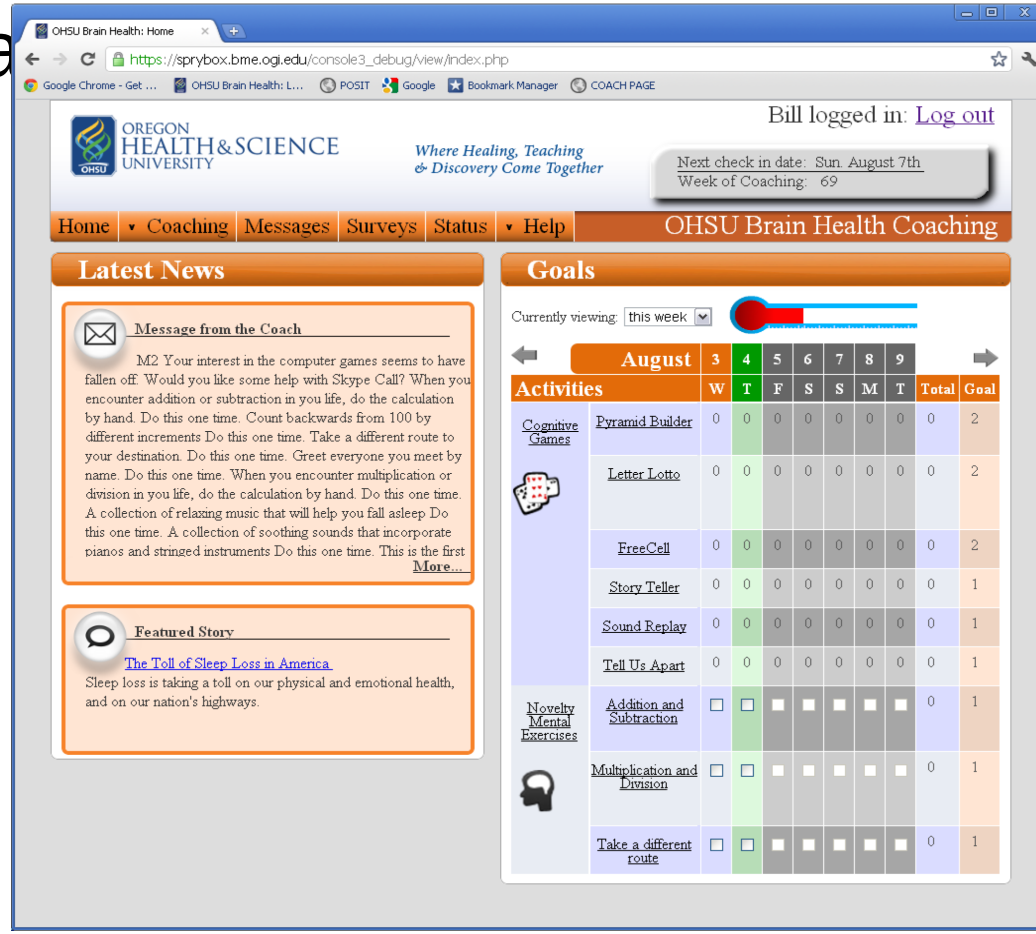
- Coaches (n=6) completed 4 coaching sessions for a panel of 10 (simulated) patients, half using automated system, half using manual system. Coaches were crossed over to alternate system after each session.
- **Efficiency** improved with semi-automated system (mean time to clear patient manual 4:26 min 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 pa

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



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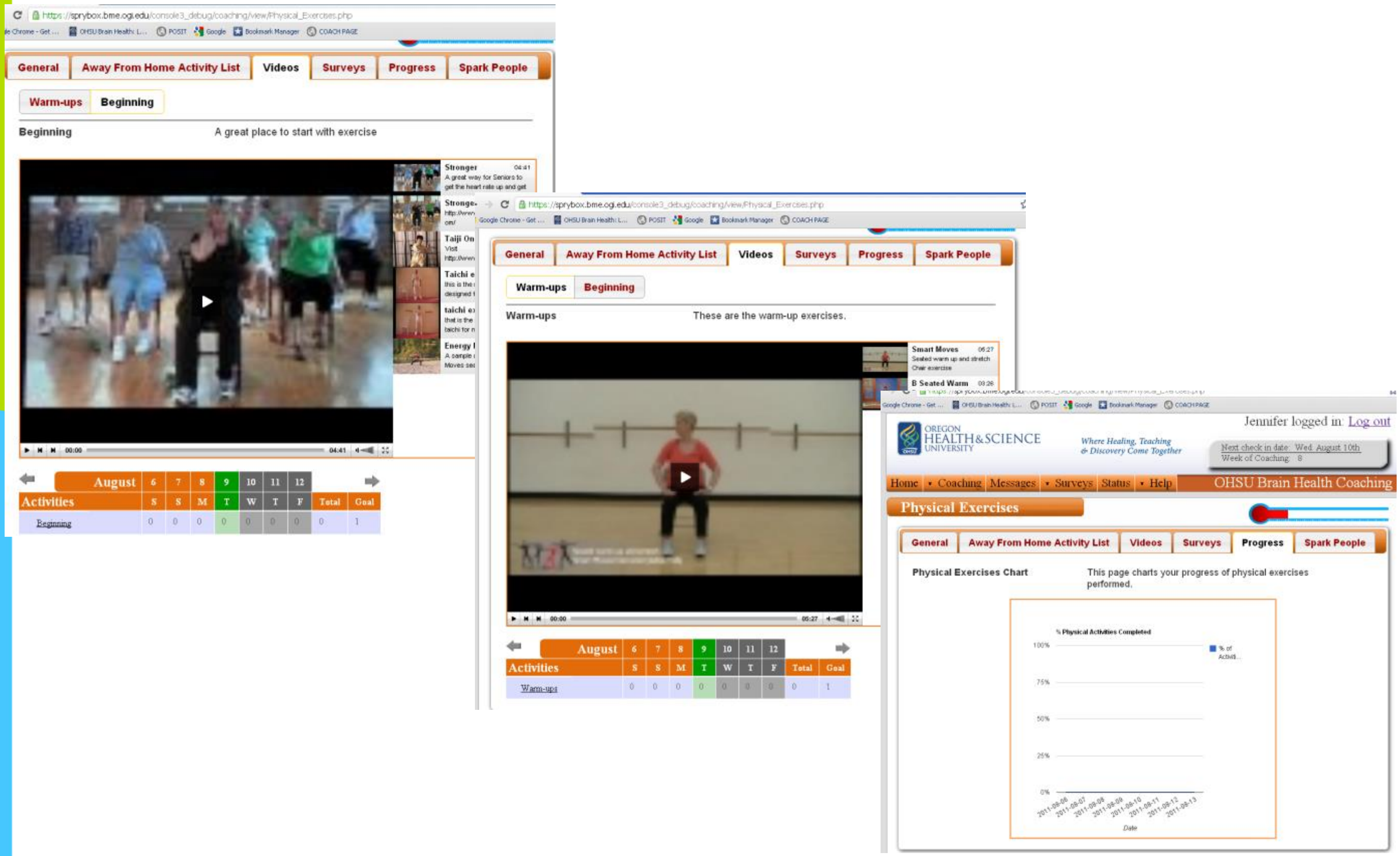
Physical Activity Module



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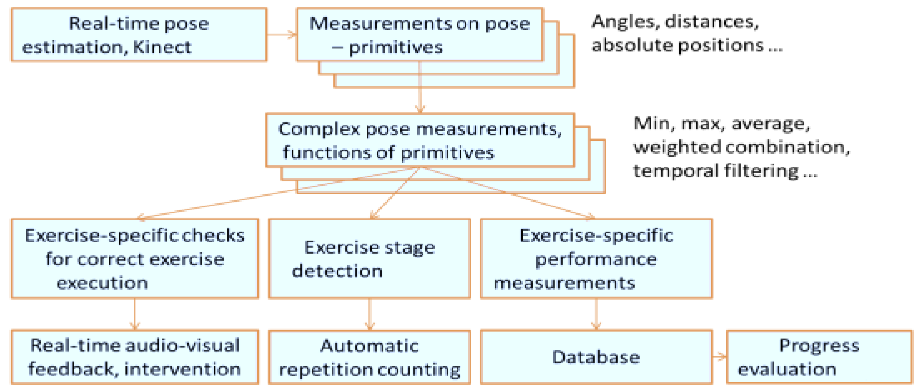
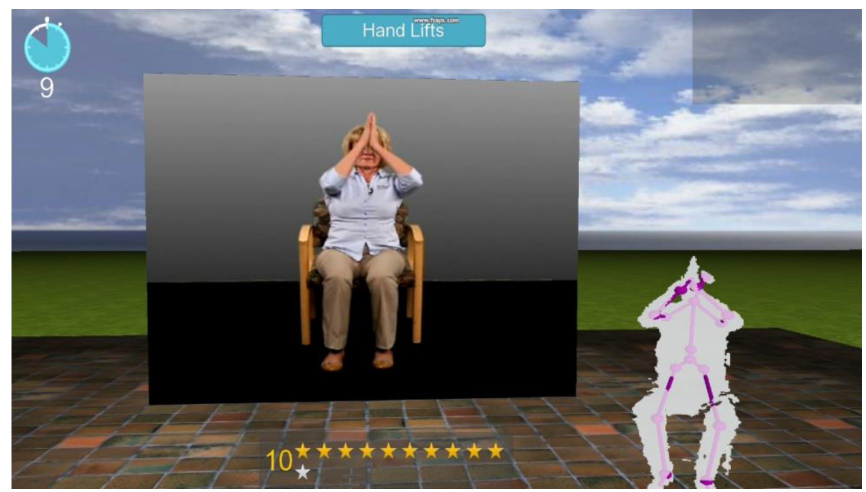
Automated Coaching for Physical Exercise

- 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





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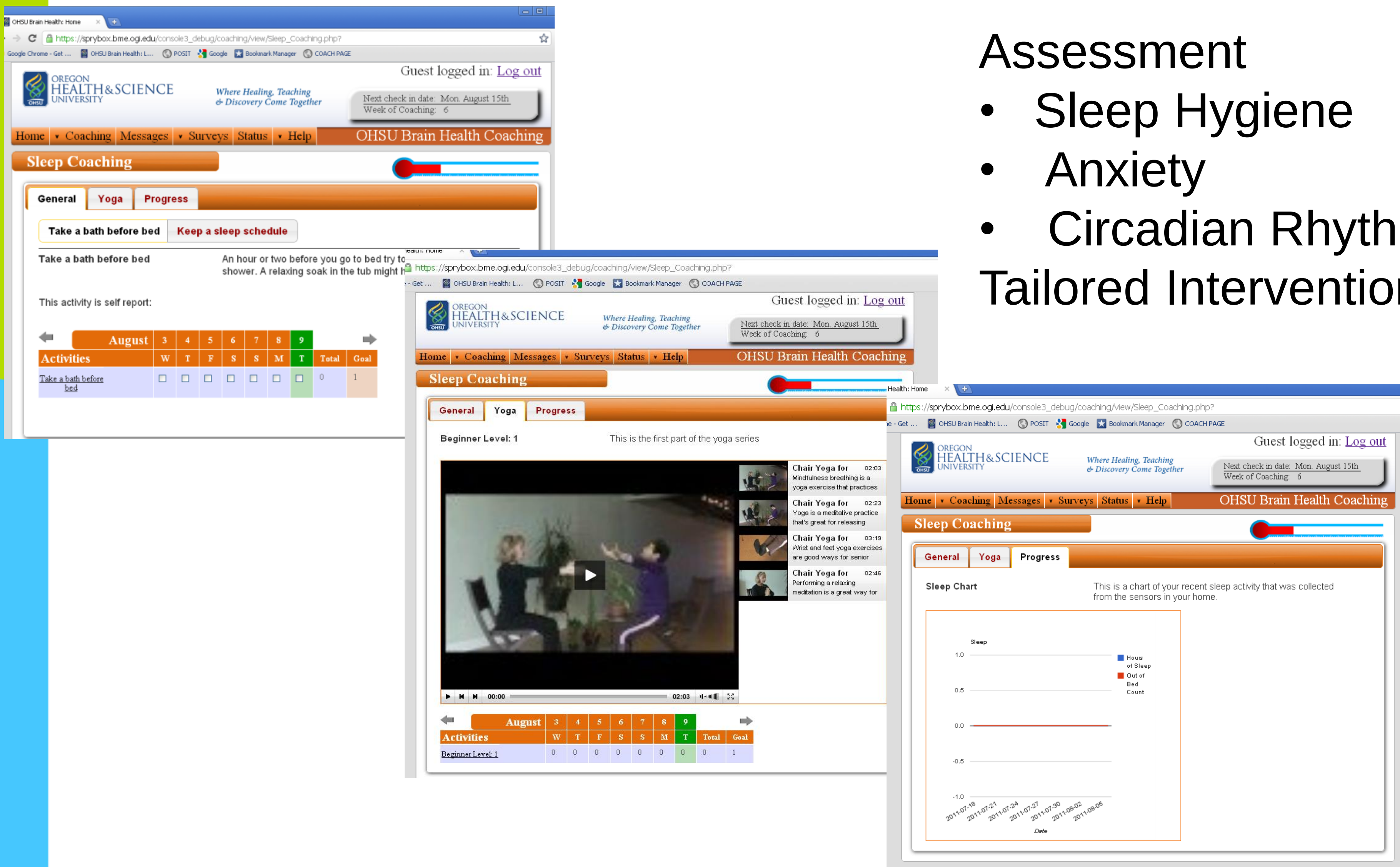
Sleep Module



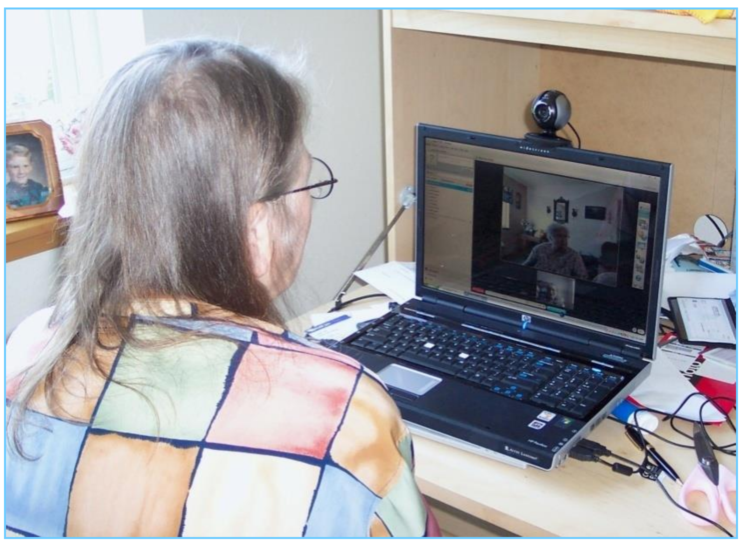
Assessment

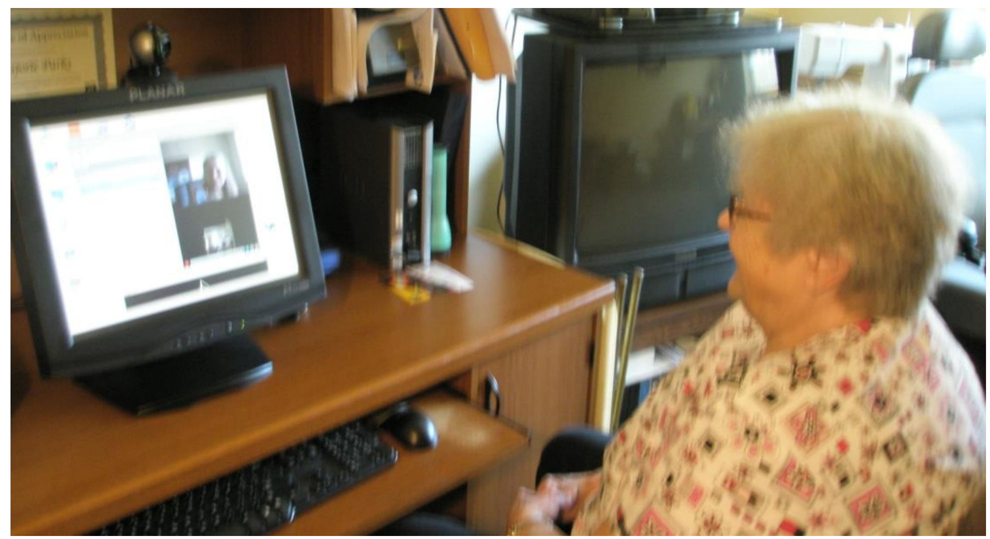
- Sleep Hygiene
- Anxiety
- Circadian Rhythm

Tailored Intervention

Socialization Intervention

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





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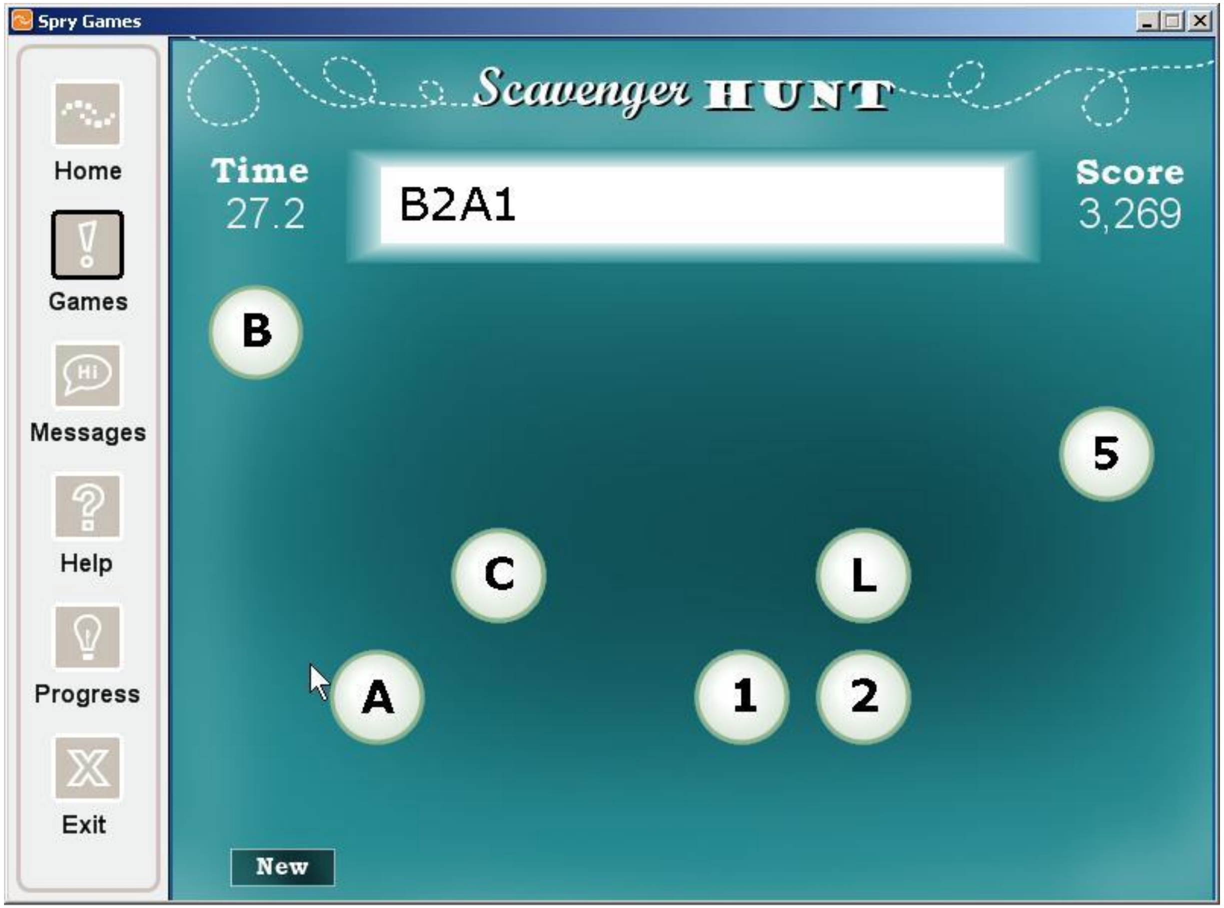
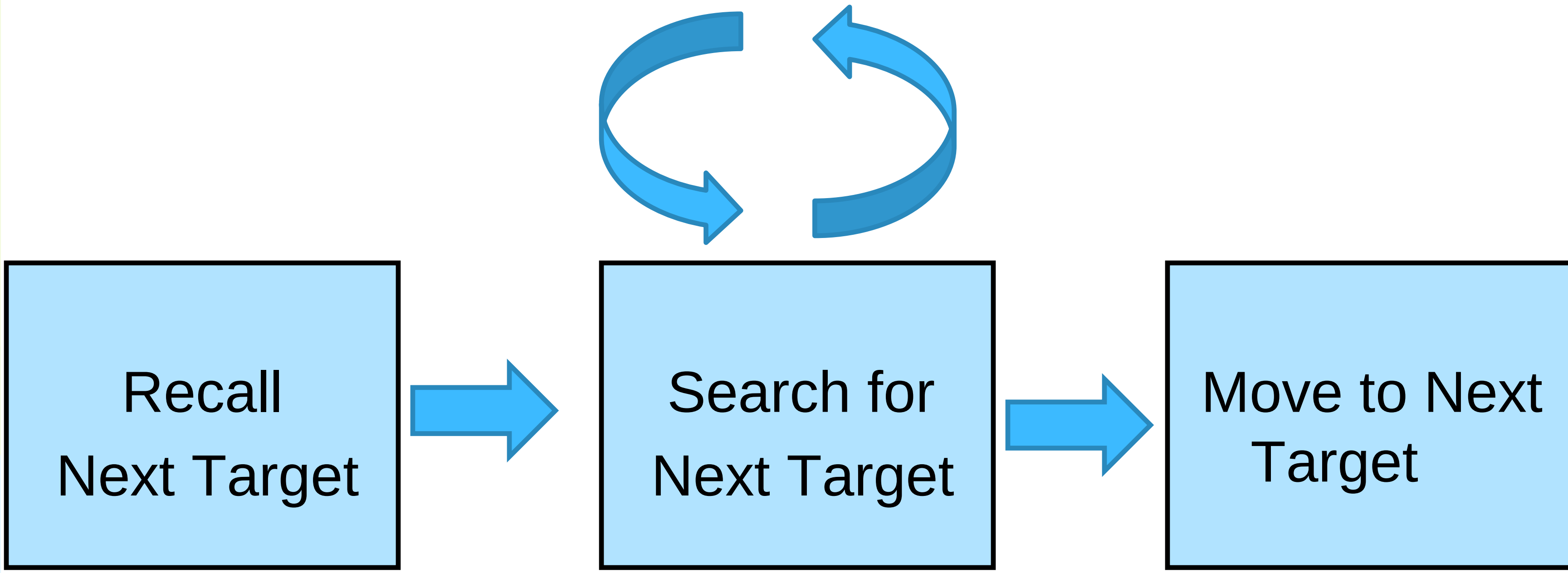
Cognitive Computer Games
(embedded cognitive metrics)

Computer Game to Measure Executive Function



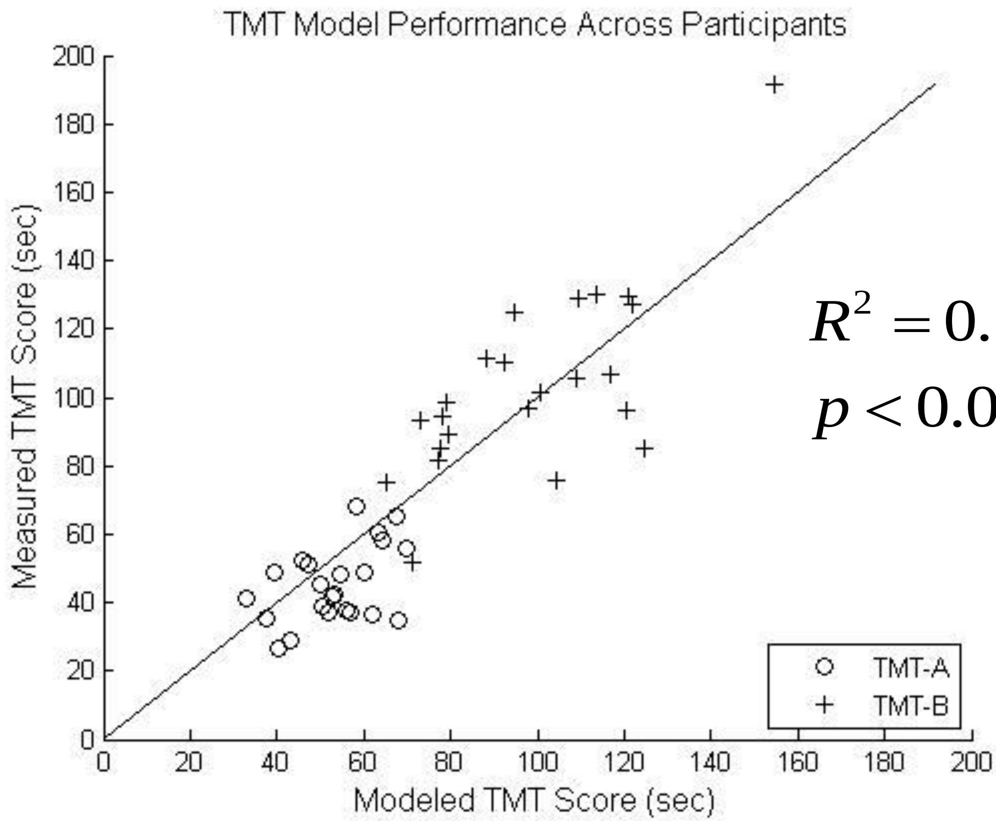
Model Recall, Search, Motor Speed



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

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.

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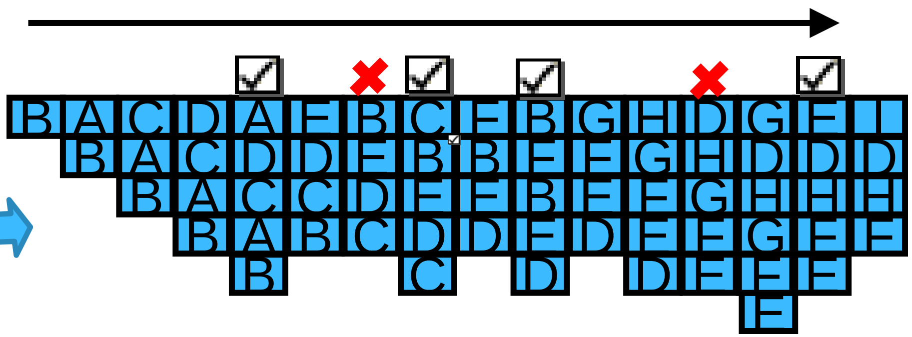
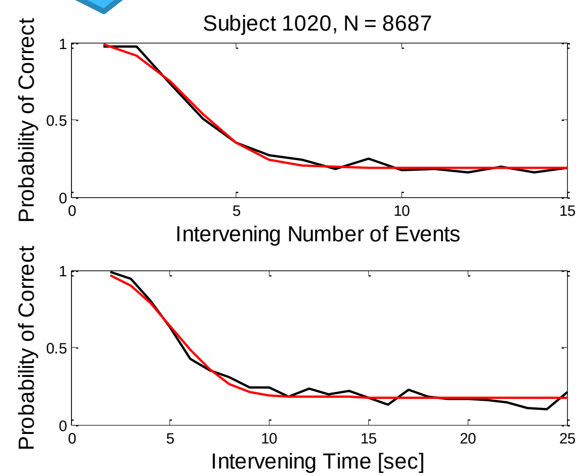
Cognitive Modeling Example: Memory



Characterize Memory Capacity

- Intervening number of events
- Intervening time
- Memory load

Simple Memory Model: Discrete Buffer



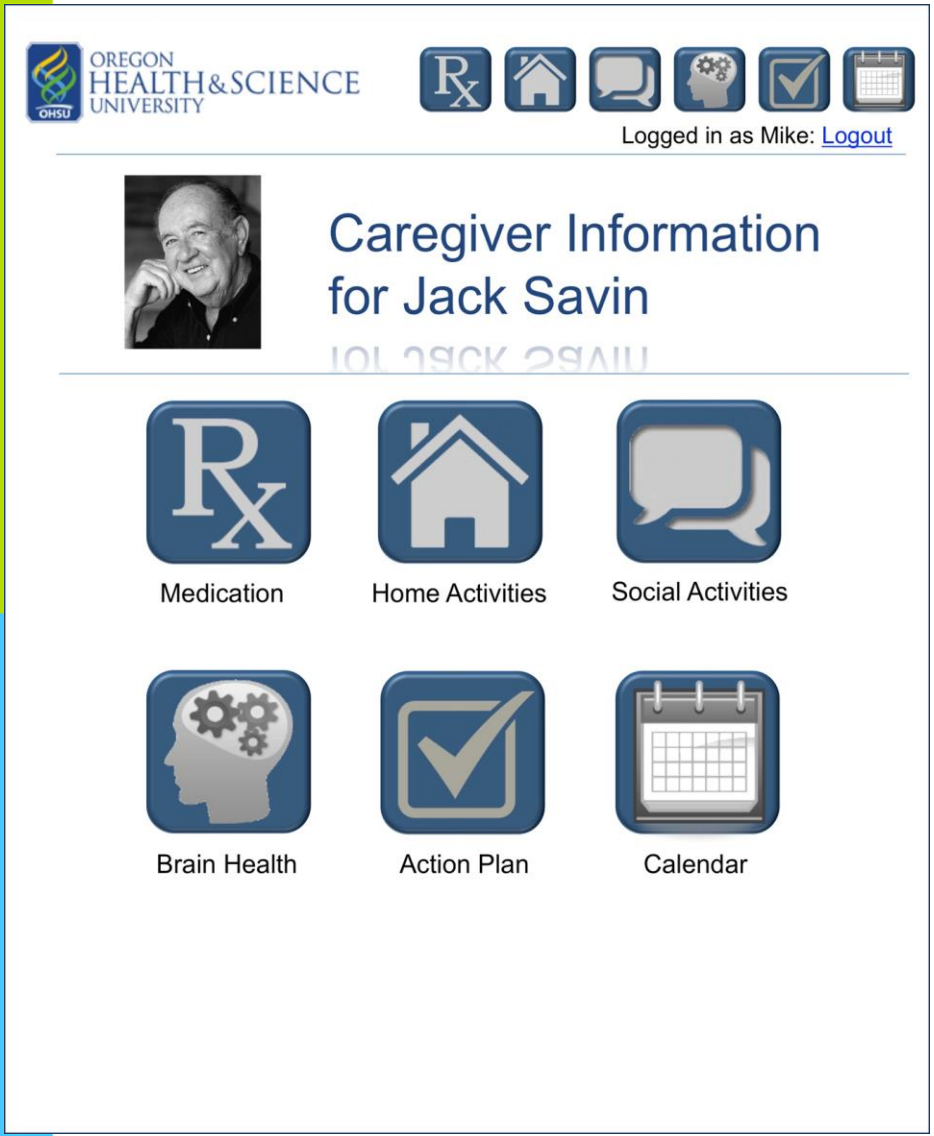
Characterize Memory Capacity with a Single Parameter

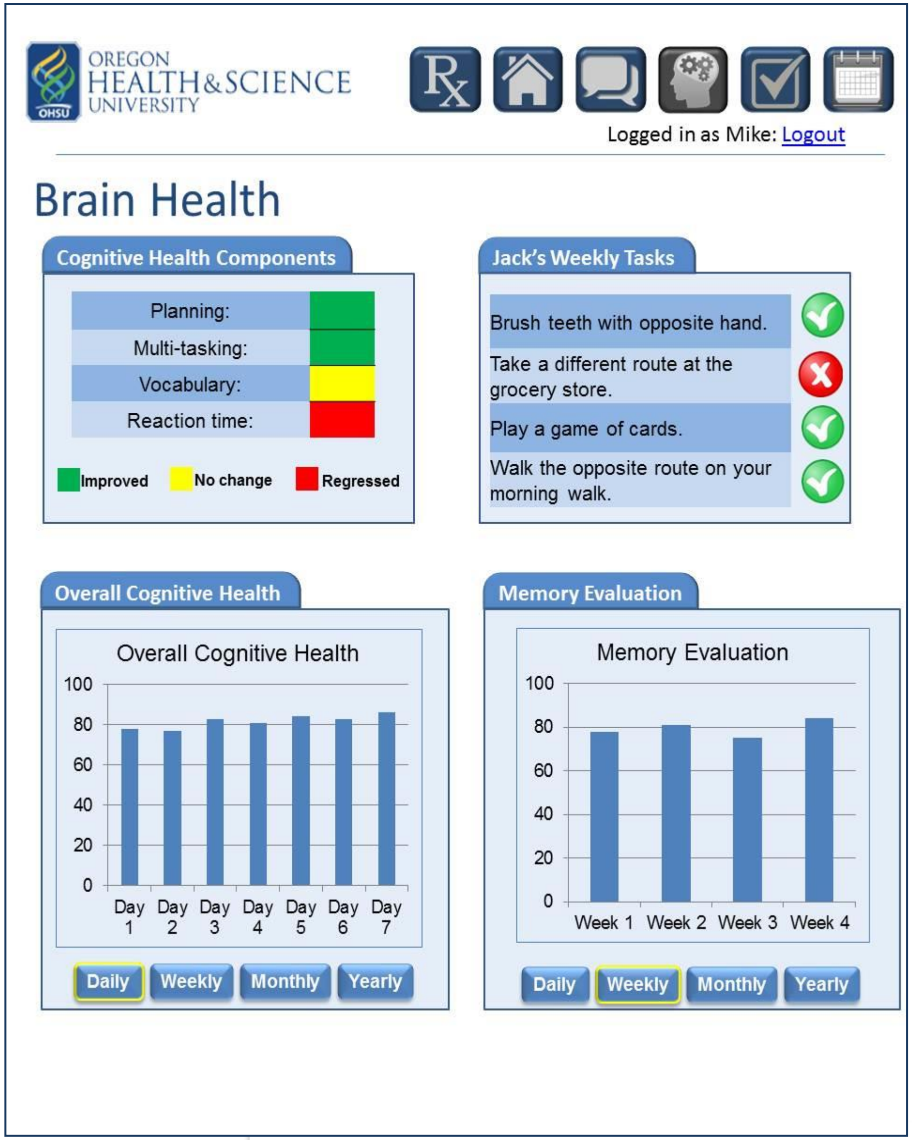
M Pavel, et al., www.ORCATECH.org

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

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.

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

Opportunities for Nursing

- Home Health and Self-Management are domains of Nursing
- New job opportunties
  - Coordination of care to the home
  - Multidisciplinary teams
  - Community health workers
- New research opportunities
  - Need to use technology to make the clinical interventions more tailored & timely

Summary:

Considerations when Designing mHealth 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

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Questions?

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