Mobile and Connected Health Technologies and Interventions

Donna Spruijt-Metz, MFA PhD

dmetz@usc.edu
Director, USC mHealth Collaboratory
Research Professor, Psychology & Preventive Medicine
University of Southern California Center for Economic and Social Research

Presented at Turning the Tide: New Directions in Health Communication
The Lerner Center for Public Health Promotion, April 27, 2018

USCDornsife Center for Economic and Social Research

USC mHealth Collaboratory

Before I start: Thanks to

FUNDERS

- **NIMHD** P60 002564
- **NSF** (IIS-1217464, 1521740)

Multiscale, Computational Modeling TEAMS

- Misha Pavel, Steven Intille, Wendy Nilsen, Benjamin Marlin, Daniel Rivera, Eric Hekler, Pedja Klasnja, Inbal Nahum-Shani

mHealth Collaboratory, ICT:

- Bill Swartout, Skip Rizzo, Arno Harthold, Luz Castillo

KNOWME TEAM

- Murali Annavaram, Giselle Ragusa, Gillian O'Reilly, Adar Emken, Shri Narayanan, Urbashi Mitra, Gautham Thatte, Ming Li, Sangwon Lee, Cheng Kun Wen, Javier Diaz, Luz Castillo

M2FED TEAM

- Jack Stankovic, John Lach Kayla De La Haye, Brooke Bell, Luz Castillo, Yadira Garcia, Meiyi Ma, Ridwan Alam, Asif Salekin, Zeya Chen, Mohsin Y. Ahmed, Abu Mondol, Sarah M. Preum, Ifat Emi

Mobile Health

- The internet of things:
  - On-body,
  - Chemical,
  - Implantable
  - Deployable,
  - All your digital exhaust
  - Persistent user interface,
- Monitoring Health
- Modifying Behavior
- in Real-Time
- and in Context

Mobile Health

Context in the 21st Century

From Point of Care

To Point of Need

In 2018, Only 11% of Adults are Not Online

Women	12%
Men	11%
Black	13%
Hispanic	12%
White	11%
18-29	2%
30-49	3%
50-64	13%
65+	34%

<30K	19%
30K—49,999	7%
50K—74,999	3%
75K+	2%
Less than HS	35%
Some HS	16%
Some College	7%
College+	3%
Urban	8%
Suburban	10%
Rural	22%

A talk in 3 parts: **mHealth^3**

Part 1: Monitoring

Part 2: Modeling

Part 3: Modifying

A talk in 3 parts: **mHealth³**

Part 1: Monitoring

Part 2: Modeling

Part 3: Modifying

M2FED: Monitoring & Modeling Family Eating Dynamics

Jack Stankovic, John Lach, Kayla de la Haye, Donna Spruijt-Metz

Students: Brooke M. Bell, Asif Salekin, Zeya Chen, Mohsin Y. Ahmed, Ridwan Alam, Jessica Rayo Abu Mondol, Meiyi Ma, Sarah M. Preum, Ifat Emi

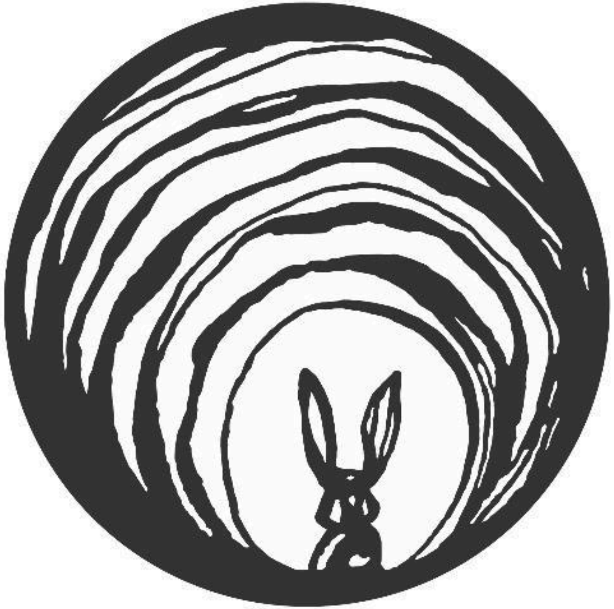
M2FED

USCDornsife Center for Economic and Social Research

NSF SCH#1521722

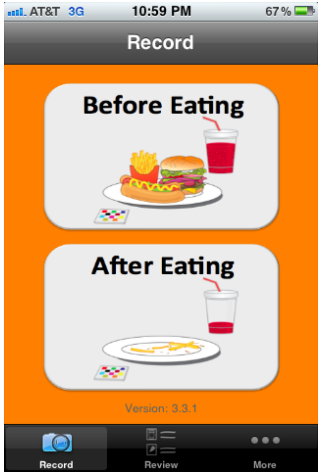
USC mHealth Collaboratory

Basic Premise:
We Don't Know Exactly What People Eat
Because we can't measure it.



Premise 1: Measuring dietary intake is *the* ‘wicked problem’ of obesity research

- Ask people



- Before eating

- After eating

24-hour recalls by interviewer (NDSR) or online (Subar et al 2012)
Diaries: Paper, apps e.g. MyFitnessPal (Patel et al 2016), pictures (Boushey et al 2016)
Food frequency by questionnaire(Talegawkar et al 2015), by EMA (Bruening et al 2016)

Premise 1: Measuring dietary intake is *the* 'wicked problem' of obesity research

- Ask people
- Observe people



Ahmad Z et al Proc IS&TISPIE 2014, Beltran et al, Proceedings, 2016,
In lab (Fisher et al, 2002), in field (Orrell-Valente et al, 2007)

Premise 1: Measuring dietary intake is *the* ‘wicked problem’ of obesity research

- Ask people
- Observe people
- Sense people (wearables, deployables)

Samsung Inc. Family Hub™

Premise 1: Measuring dietary intake is *the* 'wicked problem' of obesity research

- Ask people
- Observe people
- Sense people
- Biological measures

Garg et al 2006, Qin et al. 2017

Premise 1: Measuring dietary intake is *the* ‘wicked problem’ of obesity research

- Ask people
- Observe people
- Sense people
- Biological measures
- Grab ‘small’ data

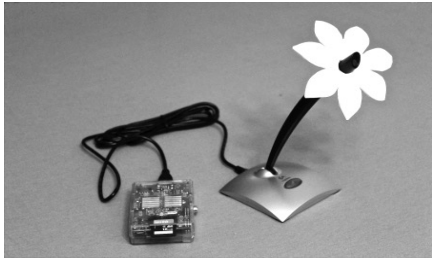
Premise 2: And even if we could be exact: Messages about dietary intake fail.

- 2015 Dietary Guidelines for Americans
  - Removes cholesterol
  - Removes limit on dietary fats
    - limited intake of healthful unsaturated fats, i.e. nuts, vegetable oils, fish
- People don’t know/remember what they ate
- Messages are confusing, shifting, impersonal
- Measures and Messages don’t take into account that eating is a **dynamic, embedded behavior**

Family eating dynamics (FED)

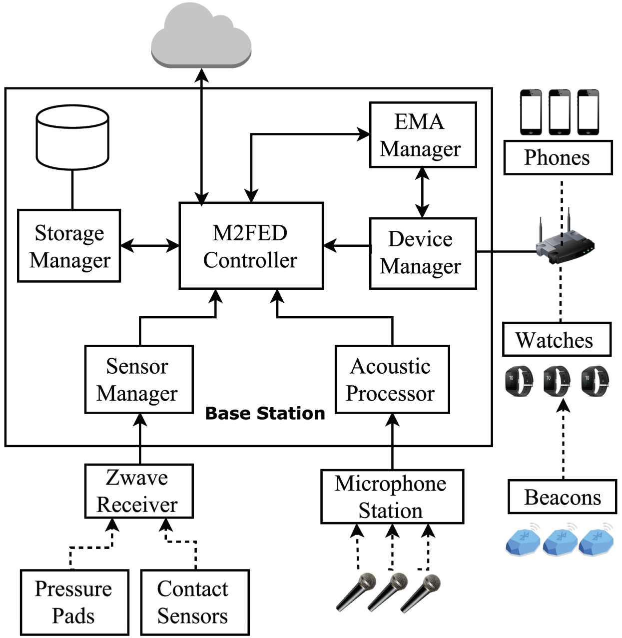
- FED influence eating behaviors
  - **Mimicry, synchrony** (Hermans et al, 2012)
  - **Modeling** (Boutelle, Cafri, & Crow, 2012)
  - **Parenting styles** (Birch, Fisher, & Davison, 2003, Lytle et al 2011)
  - **Mood** (Peters, Kubera, Hubold, & Langemann, 2011)
  - **Food environment & food choice** (Lytle et al., 2011
- FED can be changed through interventions that also impact weight (Epstein, 1996, West et al., 2010)
- Until recently, FED were only measurable through interviews, questionnaires or observation.

People as Complex Systems Embedded within Complex Systems Sensed Continuously in Context



M²FED: monitoring & modeling family eating dynamics

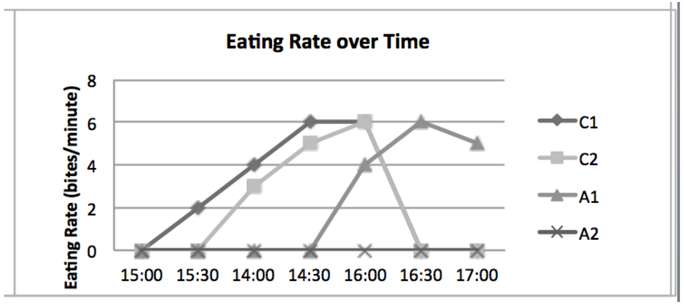
- Identify key contextual elements in the home relevant to family eating
- Cyber-physical system + Ecological Momentary Assessment (EMA)
  - Detects bites/eating events, mood, spatial location; **data** that triggers EMA



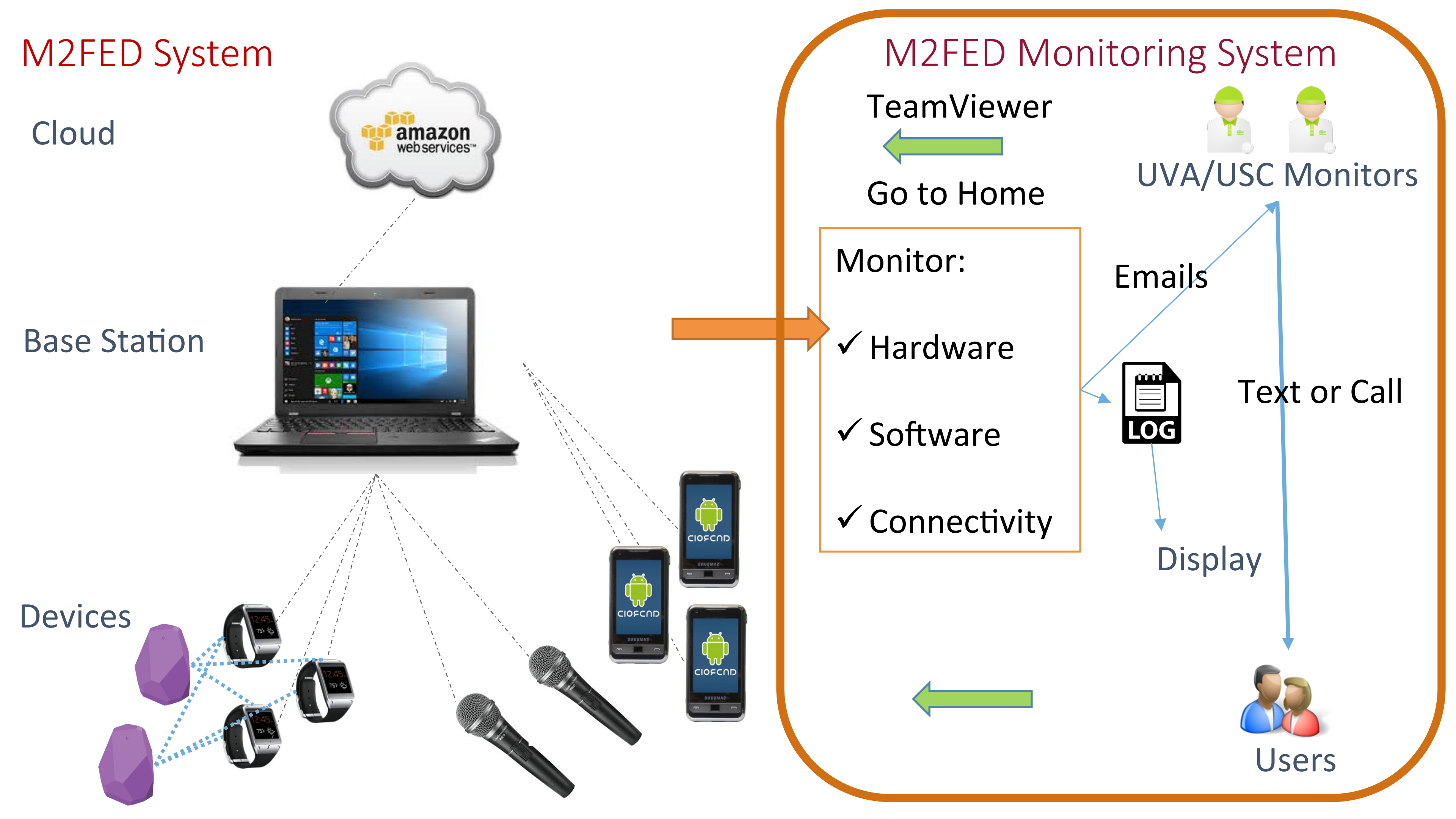
M2FED Sensor system
(calibrated in the lab, deployed in the wild)

M 2 F E D

Data



Family Member	Mood During Eating Event			Location During Eating Event		
Child 1	😐	😐	🙁	Kitchen	Kitchen	LvRoom
Child 2	🙂	🙁	🙁	Kitchen	Kitchen	Kitchen
Adult 1	🙂	😐	🙁	Kitchen	Kitchen	Kitchen
Adult 2	🙂	😐	😐	Kitchen	Kitchen	LvRoom



M2FED System
Cloud
amazon webservices
Base Station
Devices
M2FED Monitoring System
TeamViewer
Go to Home
UVA/USC Monitors
Monitor:
✓ Hardware
✓ Software
✓ Connectivity
Emails
LOG
Text or Call
Display
Users

Mood detection via voice traces

- Initial algorithms developed on existing emotion speech datasets*
- 10 Ten families visited our lab
- 15-20 minute semi-structured discussion sessions were video recorded
- Moods were manually labeled as the ground truth input for algorithm development (inter-rater reliability .70).

* EMA (Lee et al, 2005), SAVEE (Haq et al, 2010).

Eating detection using smartwatches

- Initial algorithm development: data collected during ~ 2-hour meals from 5 subjects wearing Sony smart watches.
- 31 Individual in-lab structured eating sessions,
- 12 unstructured in-lab individual eating sessions, and
- 6 unstructured in-lab meals.
- Overall accuracy (bites, eating events) between 80% -96%

Signal-Driven & Scheduled Ecological Momentary Assessment

Trigger: Sensed mood

Cause of stress, anger, happiness, sadness

Rule-based schedule

Vigor, Fatigue,

Anxiety, positive affect

Trigger: Sensed eating event

Eating in the absence of hunger

Self-regulation

Mindfulness

Trigger: Participant – reported event or mood

Text, picture, or sound recording

Ubiquitous measures

- Who is in the room (Smartwatch ID & Beacons)
- Opening of cabinets, drawers, refrigerator (Beacons)
- Speaker Identification (Trained algorithms from sound)
- Length of meal (Smartwatch)
- Speed of eating (Smartwatch)

What we want to know about eating

Where
When
With whom
Length of event
Speed

Mood

Stress and anxiety

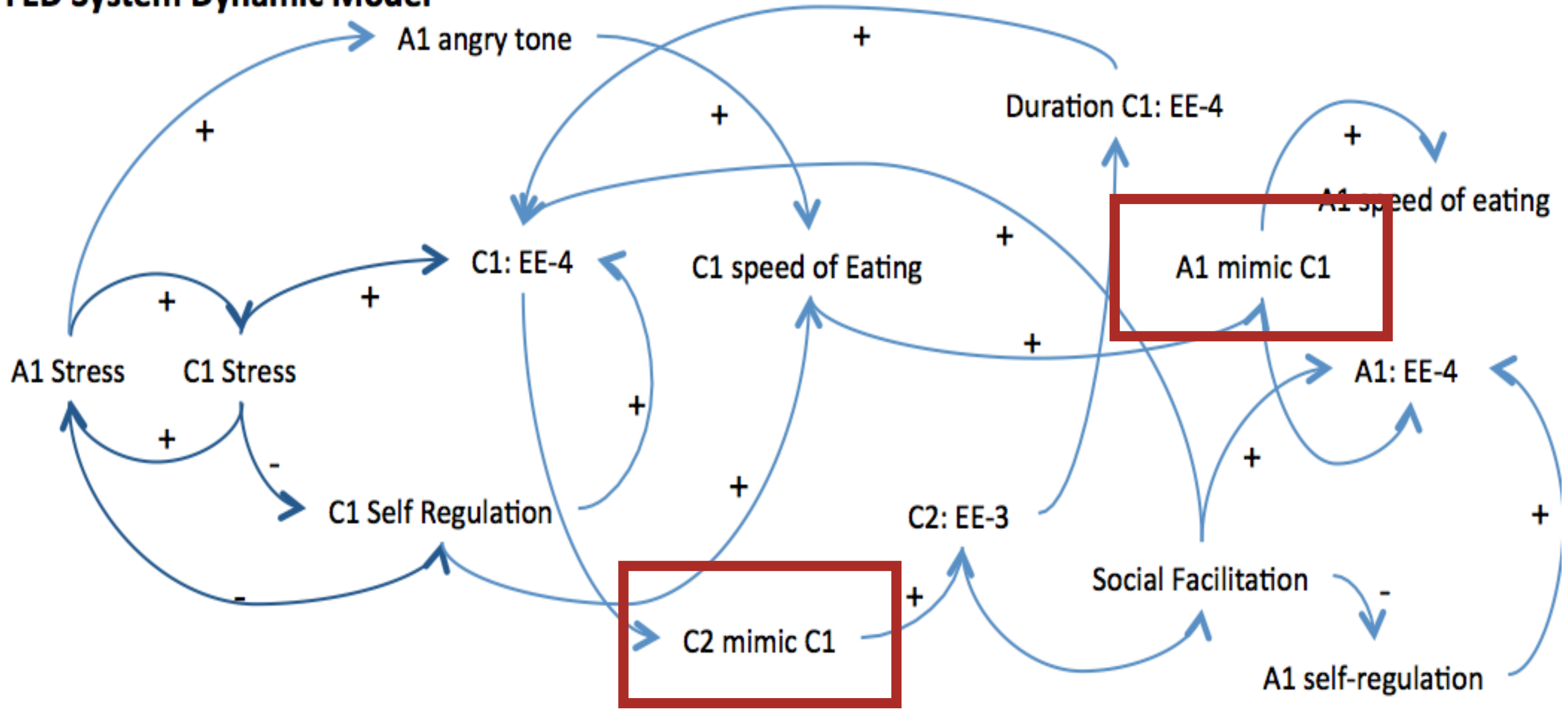
Concurrent Activities (TV, phone use)

Kitchen cabinet & refrigerator access

Eating in the absence of hunger

Prior and Post Activities

FED System Dynamic Model



Bite Mimicry

Mimicked bite (x_{ij}) = j takes a bite within x sec. after i takes a bite

Time	0:01	0:02	0:03	0:04	0:05	0:06	0:07	0:08	0:09	0:10	0:11	0:12	0:13
P_i bite	X				X		X						
P_j bite		X					X				X		

mHealth^3: Monitor, Model & Modify Behavior

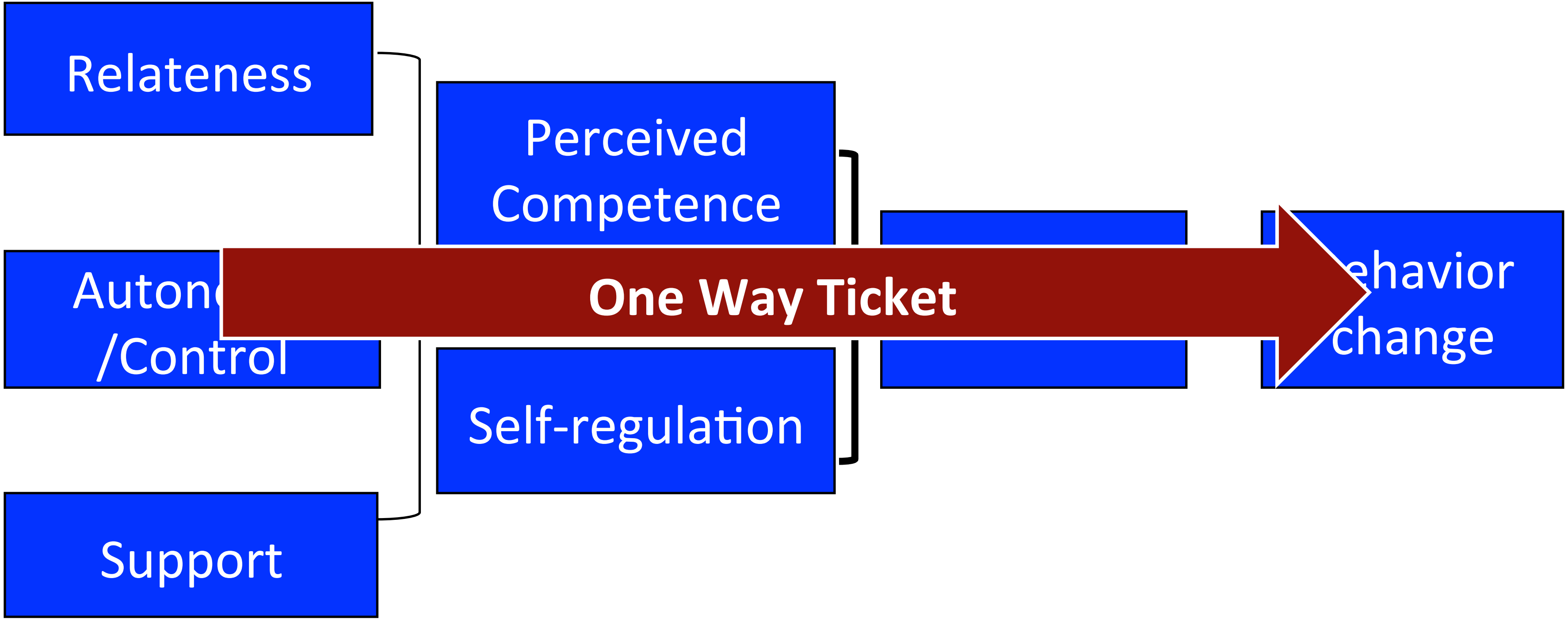
MODELING

TBM

Health behavior models in the age of mobile interventions: are our theories up to the task?

William T Riley, PhD,[1] Daniel E Rivera, PhD,[2] Audie A Atienza, PhD,[3] Wendy Nilsen, PhD,[4] Susannah M Allison, PhD,[5] Robin Mermelstein, PhD[6]

Our Current Theories are Static



TBM

ESSAY

Building new computational models to support health behavior change and maintenance: new opportunities in behavioral research

Donna Spruijt-Metz, MFA, PhD,[1] Eric Hekler, PhD,[2] Niilo Saranummi, PhD,[3] Stephen Intille, PhD,[4] Ilkka Korhonen, PhD,[5] Wendy Nilsen, PhD,[6] Daniel E. Rivera, PhD,[2] Bonnie Spring, PhD,[7] Susan Michie, PhD,[8] David A. Asch, PhD,[9] Alberto Sanna, PhD,[10] Vicente Traver Salcedo, PhD,[11] Rita Kukakfa, PhD,[12] Misha Pavel, PhD[3]


ASK
THE
RIGHT
QUESTIONS

Transdisciplinary Treasure Hunt for *Digital Biomarkers* – New variables from old/new data:

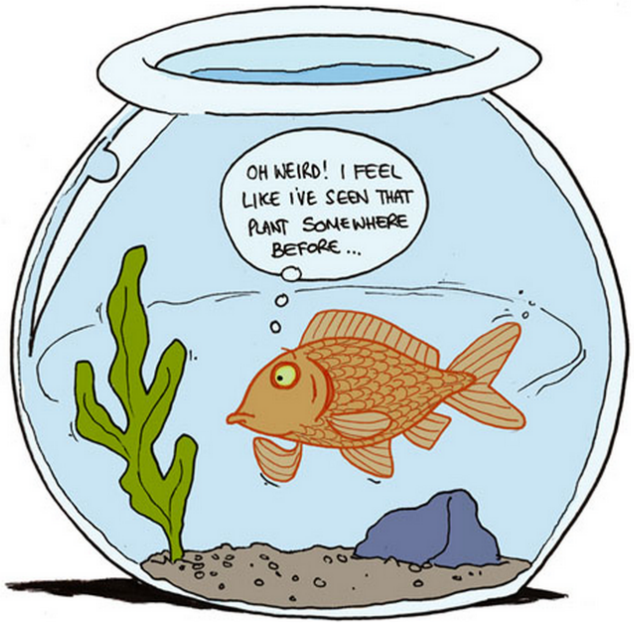
- New variables/indices/digital biomarkers that can be discovered through a mash-up of measures
- Which for which person?
- Variables in any fusion will
  - weigh heavier for some people,
  - change at different speeds
  - differ in frequency, messiness, missingness, relationships to other vars.
  - Personalizes adaptively as time-sensitive new data comes in.

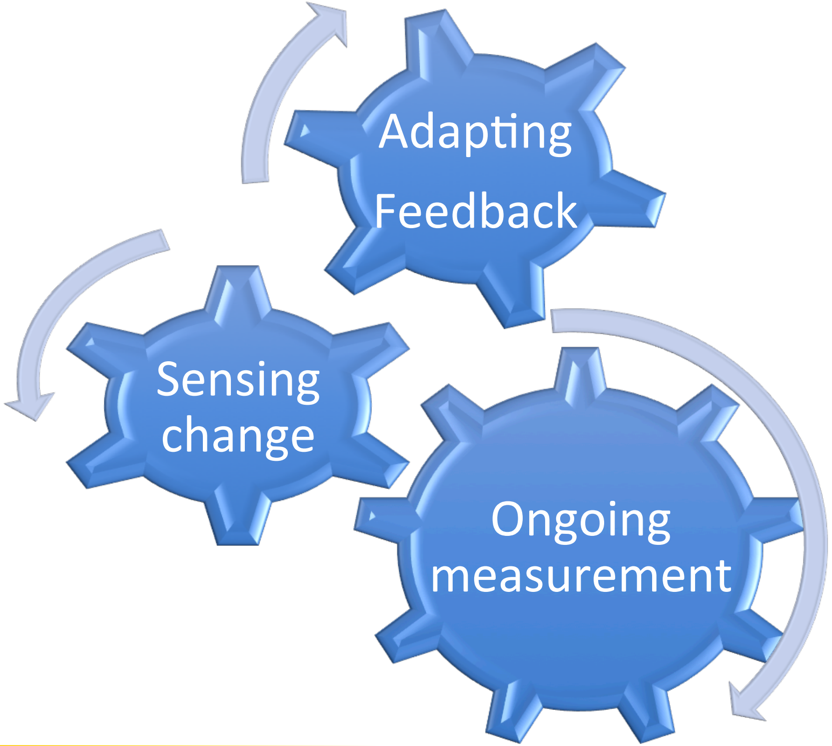
Dynamic, Multiscale Model Requirements: Idiographic vs. Nomothetic

Differences between individuals

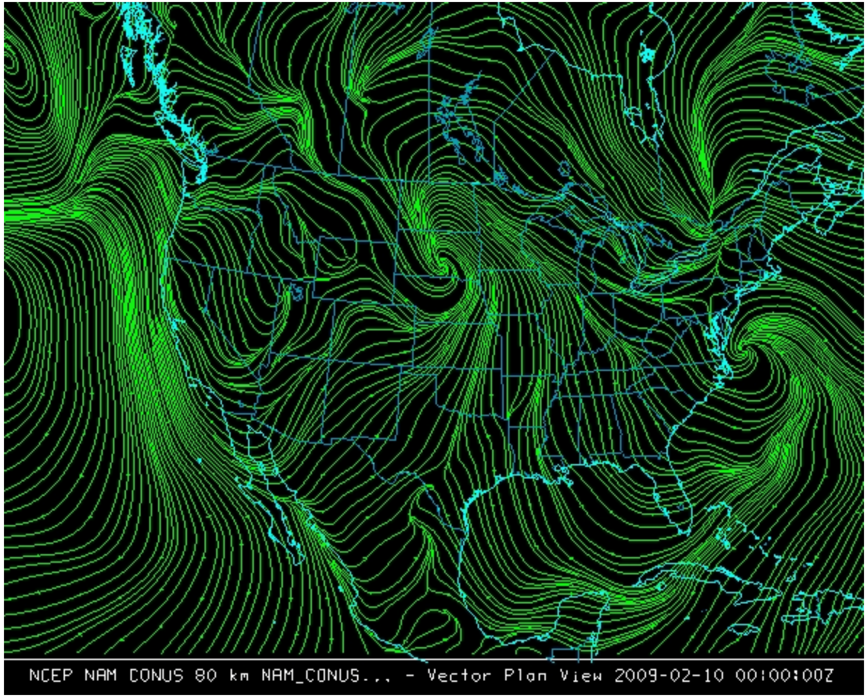
Patterns within one individual

Dynamic, Multiscale Model Requirements: Learning and adaptive





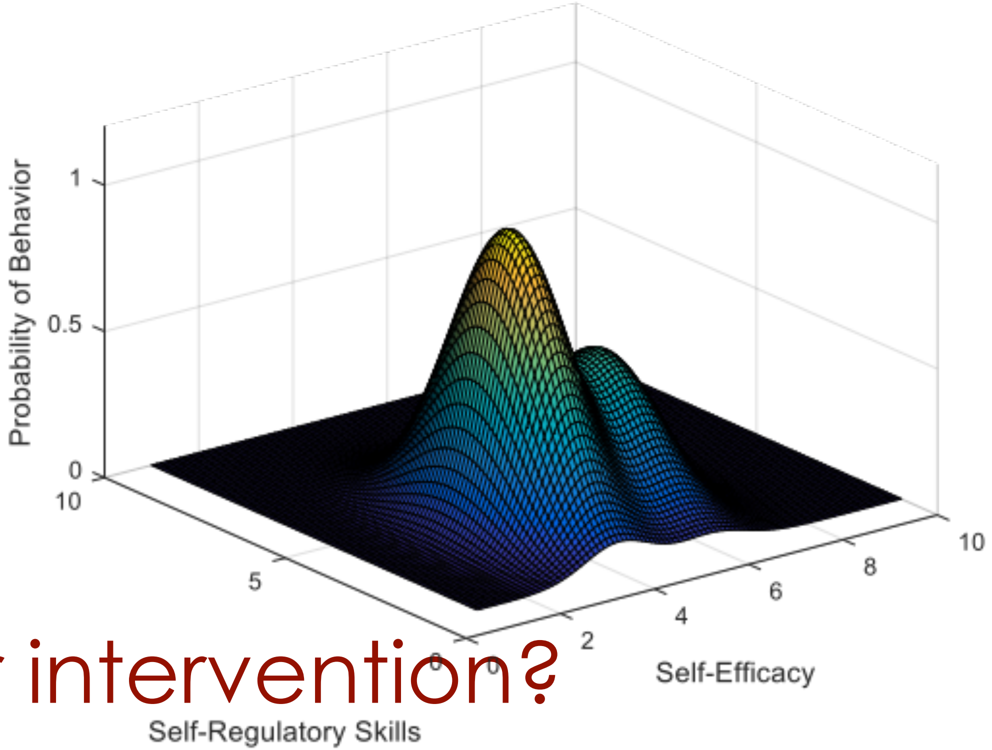
Dynamic, Multiscale Model Requirements: Conceptually seeded, yet data driven



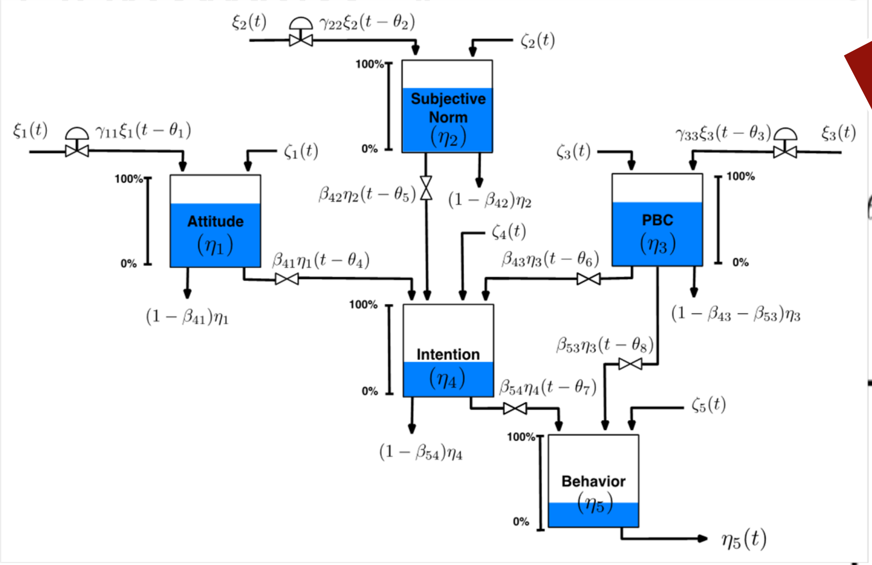
- Where are the useful signals in the current noise?
  - Semantically interesting patterns of personal & social behavior
  - A new search for meaningful mechanisms
  - Personalizes adaptively as time-sensitive new data comes in.

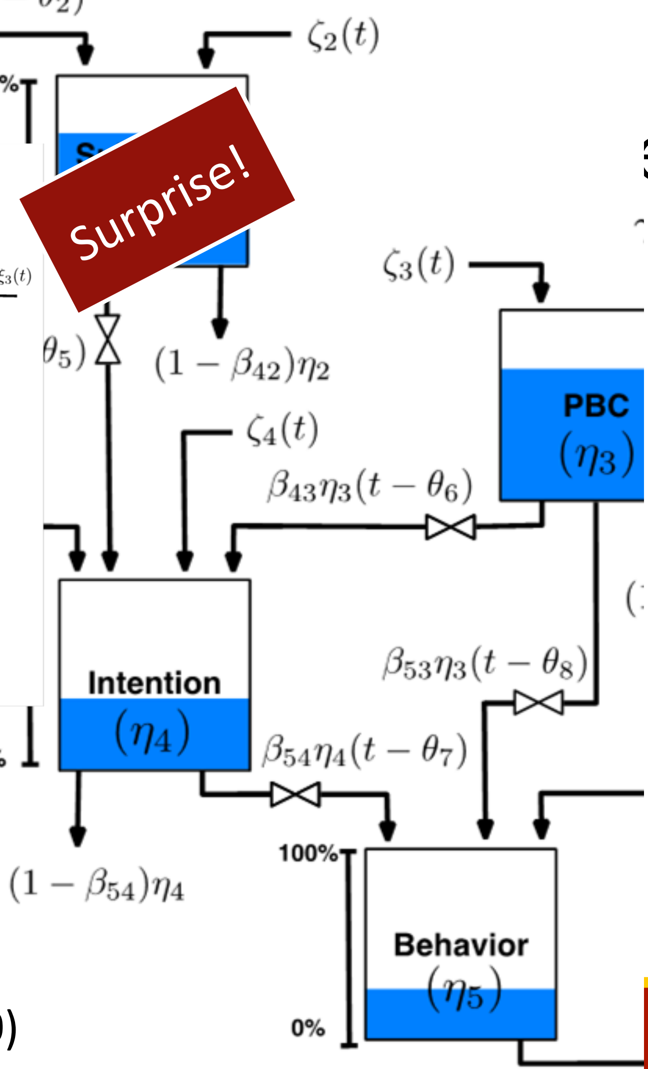
Dynamic, Multiscale Model Requirements: Multidimensional generalization spaces

- When?
- Where?
- For whom?
- In which state?
- Which dose?
- Which particular intervention?



Dynamic M ents:





Barrientos, Rivera, & Collins (2010)

mHealth^3:
Monitor, Model & Modify
health-related behavior

Modifying

Just-In-Time, Adaptive Interventions (JITAIs)

(Nahum-Shani et al, Health Psych 2015)

Intensively Adaptive Interventions (IAIs)

(Riley et al, Current Op Psych 2015)

Adaptive Interventions: 5 Elements

1. Decision Points:

    Times at which treatment options should be considered based on patient information

2. Tailoring Variable:

    Patient information used to make treatment decisions

3. Intervention Options:

    Type/dose of treatment

4. Decision rules:

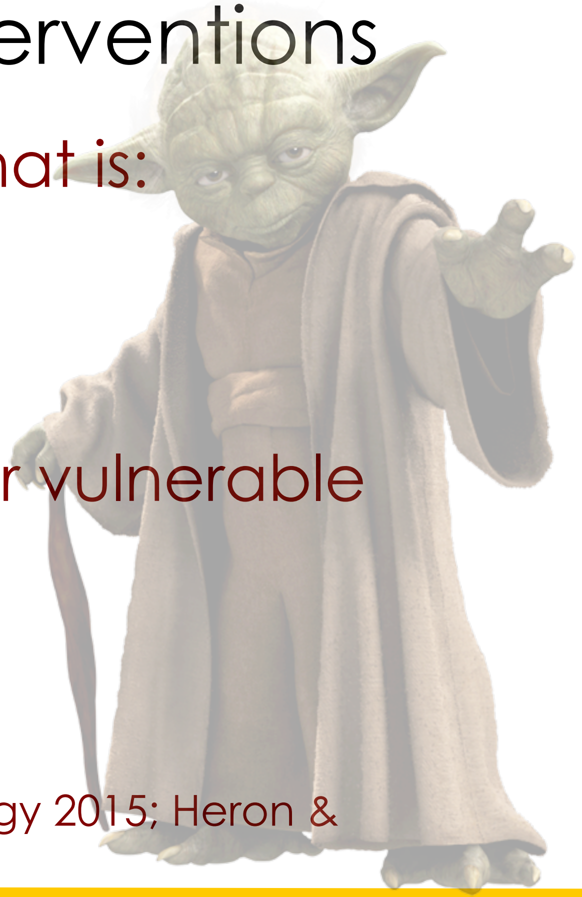
    Linking tailoring variables to intervention options

    An adaptive intervention includes multiple decision rules

5. Outcomes:

    Proximal and Distal

Just In Time Adaptive Interventions



- A JITAI is an adaptive intervention that is:
  - Delivered via mobile devices
  - Anytime
  - Anywhere
  - When the person is in need and/or vulnerable
  - When the person is receptive
  - (Meaningful Moments)

(Nahum-Shani, Hekler & Spruijt-Metz, Health Psychology 2015; Heron & Smyth, 2010; Kaplan & Stone, 2013; Riley et al., 2011)

Learning algorithms: Meaningful moments

- Receptivity[1]
- Availability[2]
- Opportune moments[3]
- Threshold Conditions[4]
  - In need and/or vulnerable
  - Receptive and/or available
  - Motivated and/or able
  - What, when, where & for whom?

[1] Nahum-Shani, Hekler, Spruijt-Metz, Health Psych 2015

[2] Sharmin, Ali, Rahman, Bari, Hossain, Kumar, UbiComp ’14

[3] Poppinga, Heuten, Boll, Pervasive Computing 2014

[4] Hekler, Michie, Spruijt-Metz et al *AJPM 2016*

USC Dornsife Center for Economic and Social Research

USC mHealth Collaboratory

KNOWME Networks

The image part with relationship ID rId3 was not found in the file.

- A suite of mobile, Bluetooth-enabled, wireless, wearable sensors
- That interface with a mobile phone and secure server
- To process data in real time,
- Designed specifically for use in overweight minority youth

The image part with relationship ID rId3 was not found in the file.

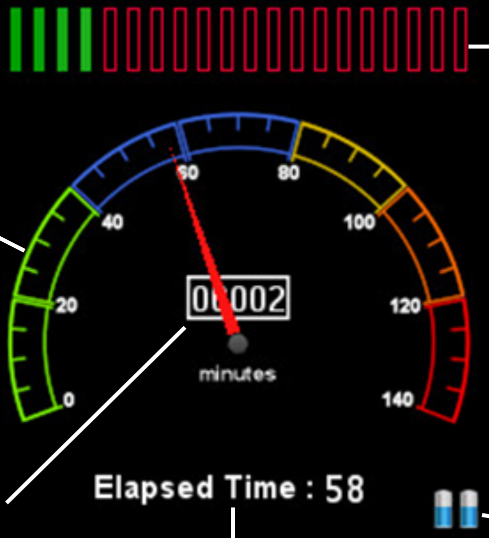
Emken et al, *Journal of physical activity & health*, 2012;
Li et al, *IEEE trans. on neural syst. and rehab. engineering*, 2010;
Thatte et al, *IEEE transactions on signal processing*, 2011

Your Activity Meter

Active Time in the Last 60 Minutes

Each bar = 30 seconds
20 bars = 10 minutes

Sedentary Time
(since the last reset)



Total Active Time

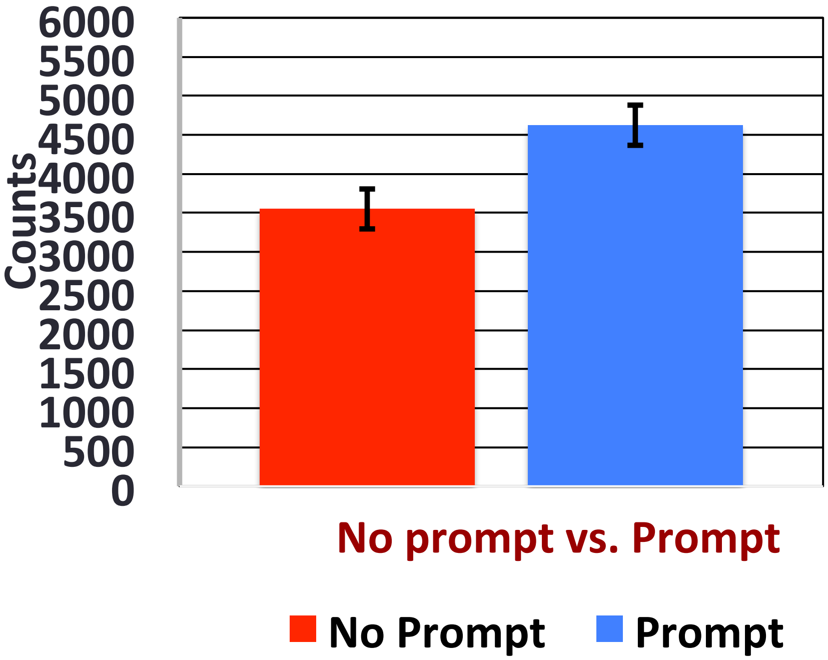
Total Elapsed Time

Battery Indicator for Each Device

Sedentary = lying down, sitting, sitting & fidgeting, standing, standing & fidgeting
Active = standing playing Wii, slow walking, brisk walking, running

Did SMS Prompts Directly Impact Subsequent Activity?

The image part with relationship ID rId4 was not found in the file.



- Accelerometer counts were 1,066 counts higher
- in the following 10 minute period
- compared to when SMS prompts were not sent ($p<0.0001$)

Thank you! Any questions?
Please stay connected!

Donna Spruijt-Metz,
dmetz@usc.edu
Also see our cool new website
http://mhealth.usc.edu