Next-gen mHealth: Integrating body sensors with smart technology to motivate health behavior change

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Center for Energy Balance Seminar

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2015 Obesity Prevalence Across US States and Territories

- 2013-2014 obesity prevalence: 38%
- No states with <20% obesity
- More than half with 30%+ obesity
The Obesity-Cancer Connection

- Obesity is now the #1 ranked cause of all cancers in non-smokers.
- 30% of cancer risk is attributed to poor diet, physical inactivity, and obesity.
- Directly and indirectly impacts cancer risk via insulin resistance, inflammation, etc.
- Weight losses of 5-10% can reduce the risk of some chronic diseases. Greater weight losses might be necessary to reduce cancer risk.
- Weight loss maintenance will likely be necessary to reduce long-term risk.
- Without more effective weight loss and health behavior change interventions the prevalence of obesity and obesity-related disease will remain high.
Children/adolescents 27%

Non-dieting adults 38%

Dieting adults 35%

2011 market billion

108 million

$148 billion in 2014
$206 billion by 2019

Diet products (meals, beverages, and supplements); Equipment (fitness and surgical equipment); and Services (e.g., Weight Watchers)
### Body-weight trajectories do not vary by intention to lose weight

<table>
<thead>
<tr>
<th></th>
<th>Intentional weight loss (36%)</th>
<th>No intentional weight loss (64%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight gain</td>
<td>31%</td>
<td>33%</td>
</tr>
<tr>
<td>Weight stable</td>
<td>30%</td>
<td>30%</td>
</tr>
<tr>
<td>Weight loss</td>
<td>39%</td>
<td>37%</td>
</tr>
</tbody>
</table>

Sorensen TI et al. (2005) PLoS Med
The current evidence-based weight control paradigm

Maintain 5%-10% loss of initial weight

Set realistic goals for weight loss and behavior change

Record food intake, physical activity, and weight

Reduce portion size, fat, and sugar

Increase fruit/vegetable intake

> 150 min/week mod-to-vig intensity exercise

Reduce energy intake by 500-1000 kcal/day

Protein intake: 12%-15%
Fat intake: ≤ 30%

Calorie restrict 1200-1800 kcal/day

Selected from over 200 LEARN program strategies (Brownell, 1989)
Look AHEAD Trial

The LOOK Ahead Trial was a multicenter randomized clinical trial comparing the effects of an intensive lifestyle intervention (ILI) to traditional diabetes support and education (DSE; the control group) on the incidence of major CVD events in over 5,000 overweight or obese men and women with type 2 diabetes.

Study goal:
7% sustained weight loss*

Recommended goal:
5% sustained weight loss

- >7% weight loss in year 1
- Steady weight regain years 2-4 with counseling 2x/month and optional monthly group sessions.
Diabetes Prevention Program

The DPP was a large, randomized clinical trial involving more than 3,000 non-diabetic US overweight and obese men and women at risk for diabetes. The trial compared the effects of an intensive lifestyle intervention to metformin and a placebo group on the incidence of diabetes.

- 6% weight loss achieved in lifestyle group after 24 intervention weeks
- Intervention effects were maintained at 1 year with monthly sessions
- Steady weight regain thereafter
Appetite-related biological and neurocognitive processes

Genetic and/or epigenetic predisposition

Societal influences

Individul Psychology

Food environment

Food consumption

Physical activity

Activity environment

Homeostatic model of energy balance

Short- and long-term energy stores; ‘energy homeostasis’

Learned behaviors and the perception of appetite-related cues

Digestion and absorption, and optimal GI signaling; ‘Hunger and Fullness’
Eating can be highly rewarding
- Celebratory or happy social settings
- Behavior modeling – food as reward
- Emotional cues – food as comfort

Learned behavior become automatic/habitual when repeated
- Environmental/food-related cues can trigger eating

Desire to eat “mistaken” for physiological hunger

In today’s plentiful food environment:
Reward homeostasis > Energy homeostasis
Learned eating behaviors

**Table 218.1** Key features of eating behavior theories

**Psychosomatic theory**
- Proposed in the late 1950s based on observations that obese individuals used food as a coping mechanism
- Emotional eating episodes are driven by pleasure and reward seeking in response to negative affect
- Low uptake of dopamine and a preference for highly palatable, energy-dense foods are the proposed mechanisms linking emotional eating to obesity

**Theory of externality**
- Proposed in the 1960s, it suggests that eating behaviors of obese individuals are driven primarily by external cues (e.g., taste of food or time of day) rather than internal cues to eat (e.g., hunger and satiety)
- External eating episodes are primarily triggered by the sensory properties of food
- Individuals who are susceptible to external cues have more food cravings and greater neuronal activity in the reward and motivation centers of the brain

**Theory of restraint**
- Proposed in 1975, it suggests that episodes of overeating and weight (re)gain are the consequences of chronic caloric deprivation
- Such episodes are triggered by situations that undermine the cognitive resolve to diet
- Two components of restraint have been identified: rigid and flexible control
- Rigid control is most consistent with the theory of restraint, whereas flexible control promotes weight control
Weight-Related Eating Questionnaire

- External Eating (5-items)
- Emotional Eating (5-items)
- Routine Restraint (3-items)
- Compensatory Restraint (3-items)

Appendix A. Weight-related eating questionnaire

Directions: Please choose a response that best expresses how well each statement describes you.

1. I purposefully hold back at meals in order not to gain weight.
2. I tend to eat more when I am anxious, worried, or tense.
3. I count calories as a conscious means of controlling my weight.
4. When I feel lonely I console myself by eating.
5. I tend to eat more food than usual when I have more available places that serve or sell food.
6. I tend to eat when I am disappointed or feel let down.
7. I often refuse foods or drinks offered because I am concerned about my weight.
8. If I see others eating, I have a strong desire to eat too.
9. Some foods taste so good I eat more even when I am no longer hungry.
10. When I have eaten too much during the day, I will often eat less than usual the following day.
11. I often eat so quickly I don’t notice I’m full until I’ve eaten too much.
12. If I eat more than usual during a meal, I try to make up for it at another meal.
13. When I’m offered delicious food, it’s hard to resist eating it even if I’ve just eaten.
15. When I’m under a lot of stress, I eat more than I usually do.
16. When I know I’ll be eating a big meal during the day, I try to make up for it by eating less before or after that meal.

Development and validation of a weight-related eating questionnaire
Susan Schembre *, Geoffrey Greene, Kathleen Melanson
Department of Nutrition and Food Sciences, University of Rhode Island, Kingston, Rhode Island, 02881, United States

Psychometric Properties and Construct Validity of the Weight-Related Eating Questionnaire in a Diverse Population
Susan M. Schembre* and Karly S. Geller*

Emotional eating and routine restraint scores are associated with activity in brain regions involved in urge and self-control
Samantha M.W. Wood a,*, Susan M. Schembre b, Qinghua He a,c, Jeffrey M. Engelmann b, Susan L. Ames d, & Antoine Bechara a

The Weight-Related Eating Questionnaire offers a concise alternative to the Three-Factor Eating Questionnaire for measuring eating behaviors related to weight loss
Brittany L. James a, Eric Loken b, Liane S. Roe a, Barbara J. Rolls a,*

Associations between weight-related eating behaviors and adiposity in postmenopausal Japanese American and white women
Susan M. Schembre a,*, Cheryl L. Albright b,c, Unhee Lim d, Lynne R. Wilkens d, Suzanne P. Murphy d, Rachel Novotny d,e, Thomas Ernst f, Linda Chang f, Laurence N. Kolonel d, Loïc Le Marchand d
Non-diet approach to improving health outcomes

HEALTHY AT EVERY SIZE

MINDFULNESS-BASED EATING AWARENESS

INTUITIVE EATING

Key assumption: People can correctly distinguish between the desire to eat and physiological hunger, if they pay attention to it.
Individuals with high vs low susceptibility to external and emotional cues (EE) “perceive” greater levels of hunger

<table>
<thead>
<tr>
<th>Subjective Appetite Ratings</th>
<th>High EE (n=30) M ± SD</th>
<th>Low EE (n=24) M ± SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fasting Hunger (mm)</td>
<td>54.5±24.2</td>
<td>38.3±26.9 p=0.016</td>
</tr>
<tr>
<td>Fasting Satiety (mm)</td>
<td>60.0±27.2</td>
<td>59.1±25.8</td>
</tr>
</tbody>
</table>

**Appetite-Related Fasting Plasma Biomarkers**

<table>
<thead>
<tr>
<th></th>
<th>High EE (n=30) M ± SD</th>
<th>Low EE (n=24) M ± SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fasting Total Ghrelin (pg/ml)</td>
<td>661.1±166.3</td>
<td>653.0±214.9</td>
</tr>
<tr>
<td>Fasting Glucose (mg/dl)</td>
<td>95.2±37.8</td>
<td>88.2±10.2</td>
</tr>
<tr>
<td>Fasting Insulin (µIU/mL)</td>
<td>11.6±10.2</td>
<td>9.1±6.4</td>
</tr>
</tbody>
</table>

Participants fasted for 12 hours
Analyses controlled for gender (28% males) and BMI (74% normal weight).

**Maladaptive eating traits are associated with a oversensitivity to hunger cues (not satiety).**

Principles/Assumptions of Hunger training

- Eating in response to hunger facilitates energy homeostasis as an intermediary step in weight regulation.

- Eating behaviors that are not regulated by physiological signals of hunger have been empirically linked to weight gain.

- Blood glucose levels are an indicator of available short-term energy

- Individuals who are obese are less sensitive to elevated BG levels;

- Decreased sensitivity to BG levels - less likely to distinguish between ‘true’ hunger and the hedonic desire to eat.

- Sensitivity to physiological hunger cues can be (re)taught.

Using glucose monitoring to self-regulate eating behavior

Hunger Training Instructions

At the first signs of hunger, before you want to eat

Measure blood glucose & record on chart

If blood glucose is at my level or below

Remember feeling of hunger

Enjoy your meal within 1 hour. If more than an hour passes, retest your glucose before eating again

Immediately after eating: record time, hunger level & food eaten on chart

If blood glucose is above my level

Delay or skip meal

Choose an activity that distracts you from food

Wait for new feelings of hunger for at least 1 hour
Hunger Training effectively reduces weight than traditional intensive lifestyle interventions

<table>
<thead>
<tr>
<th></th>
<th>Ciampolini et al. 2010</th>
<th>Jospe et al. 2015</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Pre-meal BG &lt; 85 mg/dl</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Control (n=21)</td>
<td>Cohort A (n=19)</td>
</tr>
<tr>
<td></td>
<td>All trained (n=38)</td>
<td>Cohort B (n=10)</td>
</tr>
<tr>
<td></td>
<td>Trained Low BG (n=12)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Trained High BG (n=26)</td>
<td></td>
</tr>
<tr>
<td>7 weeks of hunger training + 3 months follow-up</td>
<td>5 month changes</td>
<td>2 week changes</td>
</tr>
<tr>
<td>Pre-meal BG (mg/dl)</td>
<td>+3.6</td>
<td>Pre-meal BG &lt; 85 mg/dl</td>
</tr>
<tr>
<td>Weight loss (kg)</td>
<td>-2.3</td>
<td>Pre-meal BG ≤ fasting</td>
</tr>
<tr>
<td>Weight loss (%)</td>
<td>-3.0</td>
<td>Weight loss (kg)</td>
</tr>
<tr>
<td>Energy intake (kcals)</td>
<td>-418</td>
<td>Weight loss (%)</td>
</tr>
<tr>
<td></td>
<td>-687</td>
<td>Energy intake (kcals)</td>
</tr>
<tr>
<td></td>
<td>-668</td>
<td>-697</td>
</tr>
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Overweight and obese men and women
Goal: Provide empirical support for the principles of Hunger Training

Aim 1: Feasibility of collecting EMA data

Aim 2: Explore discordance between perceived hunger and pre-defined BG thresholds

Aim 2a: Lean vs. overweight/obese

Aim 2b: Meals vs. snacks

N=45 young men and women age 18-24 years; 38% overweight or obese
Project TwEATs event sampling results

- 7 monitoring days (N=45 enrolled)
- Eating Records (n=41 with ≥ 5d)
  - 963 eating events
  - Self-reported hunger (Yes/No)
    - 241 ‘Not hungry’ (25%)
  - Standardized BG threshold (BG < 85 mg/dl)
    - 597 > 85 mg/dl (62%)
  - Personalized BG threshold (BG ≤ fasting)
    - 494 > fasting (51%)
  - 775 BG readings
    - 80.6% of eating events

Schembre and Yuen, 2012, Appetite
Schembre et al., In press
Project TwEATs results

Summary of findings

• Lean were more sensitive than obese to pre-meal BG levels; reported being “Not hungry” at lower pre-meal BG levels (p<0.01)

• Eating when ‘not hungry’ was more likely to occur when snacking (not shown, p<0.01)

• Lean were less likely than obese to misclassify a ‘not hungry’ event (p<0.05)

• Snacks were less likely to be misclassified as a ‘not hungry’ eating event (not shown, p=0.01)

• Feasible, but 80% compliance with glucose monitoring protocol not optimal

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**Discordance rates (%)**

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Lean</th>
<th>Obese</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self-reported ‘Hungry’</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standardized BG threshold (BG&gt;85 mg/dl)</td>
<td>57.7%**</td>
<td>53.1%</td>
<td>66.9%</td>
</tr>
<tr>
<td>Personalized BG threshold (BG&gt;fasting)</td>
<td>47.7%*</td>
<td>43.8%</td>
<td>54.5%</td>
</tr>
</tbody>
</table>

** p<0.01; * p<0.05

Schembre and Yuen, 2012, Appetite
Schembre et al., Under review
Blood glucose (BG) represents short-term energy status (Campfield & Smith, 2003)

- **Pre-meal** BG indicates a biological need to eat

**Pre-to-post-meal** changes in BG results from the absorption of carbohydrates – a major dietary macronutrient

- BG dynamics as a biomarker of food intake and dietary glycemic quality

Elevated **post-meal** BG (≥ 140 mg/dl) is a risk factor for cardiovascular disease, type 2 diabetes, and diet-related cancers (Gerich et al., 2003; Liu et al., 2000; Barclay et al., 2008)

- Affects cell proliferation and tumorigenesis via modulation of the IGF axis, even in the absence of diabetes (Giovannucci, 2001 and 2007)
**Primary aim:** Examine the feasibility of collecting continuous glucose monitoring (CGM) data among free-living non-diabetic individuals

- Will healthy people wear a CGM and what do they think of it?
- Can we get useful data from the CGM?

**Secondary aim:** Explore the utility of using CGM data with the intent to provide actionable decision support for eating behaviors.

**Pre-meal BG:** To eat, or not to eat?
- Characterize eating events as occurring without physiological need

**Post-meal BG:** What was the (glycemic) quality of what I ate?
- Identify hyperglycemic responses.
- Characterize the glycemic response to foods.

**Pre-to-post-meal BG:** Did an eating event occur?
- Automating the detection of food intake.
- To what extent can we do the above without the self-report of eating.
A 7-day* free-living observational study

- **Blood glucose monitoring**: Dexcom G4 continuous blood glucose monitor (CGM)
  - CGM measures BG in the interstitial fluid via small insertable sensor.
  - BG readings every 5 minutes during wear

- **Dietary intake**: (1) time-stamped in CGM, (2) food diaries self-reported in MyFitnessPal app, (3) time-stamped food photos by mobile phones.

- **Physical activity**: (1) time-stamped in CGM, (2) self-reported in MyFitnessPal app, (3) objectively measured by accelerometer

* 5 days of data used: first 2 days are “run-in” period and data are not intended for analyses
Sample Collected Data in One Day

Sunday, November 20, 2016
10:55 AM
Oatmeal, milk, coffee (GL=39)

1:51 PM
Turkey sandwich, lima beans, Cheetos (GL=35)

6:55 PM
Rice, chicken, squash, zucchini, beer (GL=35)

8:22 PM Ice cream (GL=8)

8:56 PM Popcorn (GL=20)

9:45 PM Beer (GL=40)

• 24 non-diabetic participants, 24 to 64 years old (M = 34.75, SD = 11.30), 75% female, 33.3% normal weight, 45.8% overweight, and 20.8% obese

GL=Glycemic load, estimated from Nutrition Data System for Research (NDSR) based on food record from MyFitnessPal.
Sample Collected Data in One Week
Summary of findings: Participants on average reported 29 (SD = 11.8) eating events across the 5 analytical days

- 62.0% of those eating events occurred when BG > 85 mg/dL
- 43.5% occurred when BG > personalized fasting level
- Overweight or obese vs. lean had significantly more eating events occurring at a BG that was above the standardized threshold.
- On average, participants had 3 (SD = 4.4) hyperglycemic events

Results from Project SENSE

Eating events occurring at BG > 85 mg/dL by weight status

<table>
<thead>
<tr>
<th>Weight Status</th>
<th>Normal Weight</th>
<th>Overweight/Obese</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eating events occurring at BG &gt; 85 mg/dL</td>
<td>[Graph showing percentage difference]</td>
<td></td>
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</tbody>
</table>

Frequency of hyperglycemic events by BMI status

<table>
<thead>
<tr>
<th>BMI Status</th>
<th>All</th>
<th>BMI&lt;25</th>
<th>BMI≥25</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hyperglycemic events (freq.)</td>
<td>2.9±3.0</td>
<td>2.5±2.4</td>
<td>3.2±3.5</td>
</tr>
</tbody>
</table>

Schembre et al., In preparation
Rate of change in BG 30 minutes after a self-reported eating event are greater than in the 30 minutes prior to eating (p<0.001).

60 minute BG AUC vary by the computed glycemic load of a reported eating event (p<0.001).
Participants’ Experience with CGM

- 92% of participants agreed that the CGM device “was easy to use”
- 88% of participants agreed that the CGM sensor “was comfortable to wear”
- 64% of participants indicated that they would be willing to use a CGM device to help them achieve their health and wellness goals
- 91% indicated they would do so if the CGM sensor was non-invasive
Selected process evaluation data

“Usability: This tool is easy to use and user friendly.”

- CGM Sensor: Strongly Agree (5) 54%, Agree (4) 46%, Neither agree nor disagree (3) 4%, Disagree (2) 0%, Strongly Disagree (1) 0%
- CGM Receiver: Strongly Agree (5) 8%, Agree (4) 46%, Neither agree nor disagree (3) 4%, Disagree (2) 0%, Strongly Disagree (1) 0%
- MyFitnessPal: Strongly Agree (5) 58%, Agree (4) 33%, Neither agree nor disagree (3) 4%, Disagree (2) 0%, Strongly Disagree (1) 0%
- Accelerometer: Strongly Agree (5) 54%, Agree (4) 25%, Neither agree nor disagree (3) 8%, Disagree (2) 13%, Strongly Disagree (1) 0%
- Food Picture: Strongly Agree (5) 54%, Agree (4) 38%, Neither agree nor disagree (3) 8%, Disagree (2) 0%, Strongly Disagree (1) 0%

“Convenience: This tool is convenient for me to use in my everyday life.”

- CGM Sensor: Strongly Agree (5) 54%, Agree (4) 21%, Neither agree nor disagree (3) 21%, Disagree (2) 8%, Strongly Disagree (1) 0%
- CGM Receiver: Strongly Agree (5) 21%, Agree (4) 25%, Neither agree nor disagree (3) 17%, Disagree (2) 0%, Strongly Disagree (1) 0%
- MyFitnessPal: Strongly Agree (5) 46%, Agree (4) 29%, Neither agree nor disagree (3) 4%, Disagree (2) 8%, Strongly Disagree (1) 0%
- Accelerometer: Strongly Agree (5) 33%, Agree (4) 33%, Neither agree nor disagree (3) 17%, Disagree (2) 21%, Strongly Disagree (1) 0%
- Food Picture: Strongly Agree (5) 50%, Agree (4) 25%, Neither agree nor disagree (3) 13%, Disagree (2) 13%, Strongly Disagree (1) 0%
Future Directions

SENSE 2.0: Automating food intake detection
• Just-in-time adaptive interventions
  • Personalized diet (and physical activity) feedback
  • Proactive decision support for people with diabetes
  • Weight control

Take CHARGE: Choosing Health and Cancer Risk Reduction through Good Eating and Exercise (NIH/NCI R21)
• Adding Hunger Training to the Diabetes Prevention Program (DPP)
• 50 obese women at risk for breast cancer
• 16 week pilot intervention
• Goal: Test synergistic effect of hunger training and DPP on weight loss
  • Feasibility of integrating hunger training (via CGM) into a ILI
  • Effects size estimates on weight loss (and cancer-related plasma biomarker outcomes)
• Future large-scale RCT will examine weight maintenance outcomes
Advancing health behavior interventions

• **Thrust 1:** Mobile Sensor Data-to-Information

• **Thrust 2:** Mobile Sensor Information-to-Knowledge
  – Decision making
  – JITAI

• **Thrust 3:** MD2K – Computation

• **Thrust 4:** MD2K-Applications

MD2K
https://www.youtube.com/watch?v=uSQn2puExxM#action=share
Advancement in wearable sensor technologies has automated the self-monitoring and feedback process.

Use body sensors to unobtrusively and automatically detect health behaviors.

Process the data through algorithms designed to quantify current performance.

Enhance the bi-directional communication between participants/patients and researchers.

Deliver messages that prompt healthy decision making at critical moments to achieve health-related goals.

Sensors that measure health-related biomarkers could be used to define critical moments – glucose, heart rate variability.
A new paradigm shift in behavior change science

- Sensor-based, real-time interventions reflect a new paradigm shift in behavior change science.

- How do we get the most of just-in-time interventions?

- How do we optimize the delivery of real-time feedback?
  - Timing
  - Content

- Optimization of real-time feedback content and timing and frequency
  - Micro-randomization – timing and frequency
  - Multiphase optimization strategy (MOST) – content
Objective

- Synthesize data on the content characteristics of real-time feedback used in energy balance-related behavior change interventions
- Propose a framework for the design of real-time feedback in future interventions.

Theoretical foundation

- Control Theory - behavior is goal-driven; behavior change occurs in response to feedback on current performance relative to a behavioral goal.
- Feedback Intervention Theory - feedback motivates behavior change by focusing one’s attention on the behavioral task itself.

Schembre and Liao, Under Review
Included studies

- N=32 intervention studies published through 2016
  - Physical activity (47%)
  - Diet and physical activity (41%)
  - Diet only (9%)
  - Self-weighing (3%)
4 key characteristics of real-time feedback

- Consistent with Control Theory 4 key characteristics emerged:
  - **Timeliness** of feedback
    - Continuous feedback 31%
    - Multiple times of day 10%
    - Daily 69%
  - Level of **personalization**
    - Team-based feedback 3%
    - Person-level feedback 97%
  - **Goal-orientation**
    - Self-selected, incremental, or adaptive goals 38%
    - Static/standardized recommendations 38%
  - **Action-orientation**
    - Included explicit communication of what to do and how and when to do it 16%
Real-time feedback efficacy

<table>
<thead>
<tr>
<th></th>
<th>Significant effects (n=4)</th>
<th>Non-significant effects (n=5)</th>
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<tbody>
<tr>
<td>Timely*</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Personalized</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Continuously-available</td>
<td>75%</td>
<td>20%</td>
</tr>
<tr>
<td>Goal-oriented</td>
<td>75%</td>
<td>60%</td>
</tr>
<tr>
<td>Actionable</td>
<td>75%</td>
<td>40%</td>
</tr>
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*Study inclusion criteria

Real-time feedback that is continuously-available, personalized, and actionable relative to a known behavioral objective or goal is prominent in intervention studies with significant behavior change outcomes.
Testable model for real-time feedback content design

Real-Time Behavioral Objectives

Goals
- Reflects a desired outcome.
- Self-selected, adaptive, or standardized.
- Incrementally achieved over the day.

Targets
- Intermediate marker of a desired outcome.
- Pre-set range or threshold.
- Maintained within a specific time-interval or moment-to-moment.

Key Feedback Components

Timely
- Reflects recent behavior.
- Aims to improve the likelihood of meeting goal/target.
- Communicated passively (vs. user-initiated) to proactively motivate behavioral adjustments.

Personalized
- Based on the individual's own performance.
- Aims to redirect one's attention to their current performance relative to a behavioral goal/target.
- Communicated visually as graphs/charts or quantified verbally or as text.

Actionable
- Specifies an action plan (WHAT, WHEN, and HOW).
- Aims to reduce the discrepancy between current performance and the behavioral goal/target.
- Communicated as a behavioral prompt.

Assessment
- Cognitive load: Passive monitoring vs. self-monitoring
- Quality: Objective vs. self-reported
- Frequency: Continuous vs. specified intervals

Schembre and Liao, Under Review
Considerations for future mHealth interventions

- Objective vs. subjective data
- Privacy concerns
  - Big brother
  - People trust doctors to keep information confidential
- HIPAA compliance
  - Compromised transmission of PHI
- Security issues
  - Third-party hackers
  - Terrorist threat
Acknowledgments

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- R25 University of Hawaii Cancer Center
- T32 University of Southern California
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- Karen Basen-Engquist, MPH, PhD
- Kimberly Claiborne
- Carrie Daniel-MacDougall
- Menton Deweese, PhD
- Danika Dirba
- Genevieve Fridlund Dunton, MPH, PhD
- Karly Geller
- Troy Gilchrist
- Jimi Huh, PhD
- Bryan Juan, MPH
- Stefan Keller, PhD
- Jacqueline Kerr, MPH, PhD
- Jennifer Ng
- Munazza Noor, MS
- Yue Liao MPH, PhD
- Christine Ranieri, MS, RD
- Donna Spruijt-Metz, PhD
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