Developing mHealth Interventions to Change Behavior

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Overview

1. mHealth context: motivation, evolutionary pace, digital divide

2. What is the evidence that mHealth interventions work?

3. Getting mHealth tools to harness behavior change mechanisms better

4. Optimizing the mHealth intervention suite
Why use mHealth technology for behavior change?

1. Population reach
   - Overcome access/logistical barriers (distance, time, parking, childcare, lack of local expertise)

2. Lowered human interventionist cost, scalability, maintenance (after initial implementation)

3. Potential for contextualized ("smart") feedback and in-the-moment support, in natural environment,
“Get Smart” – TV Secret agent 1960s

- Processing speed
- Memory capacity
- Sensors
But what about the digital divide?

“Today high speed broadband is not a luxury, it’s a necessity.” – President Obama, January 14, 2015
Mobile = Game Changer

**Smartphones are more common in U.S., Europe, and the Middle East**

*Regional medians of adults who report owning a smartphone, cellphone but NOT smartphone, or no cellphone.*

<table>
<thead>
<tr>
<th>Region</th>
<th>Smartphone</th>
<th>Cellphone but NOT smartphone</th>
<th>No cellphone</th>
</tr>
</thead>
<tbody>
<tr>
<td>U.S.</td>
<td>72%</td>
<td>19%</td>
<td>9%</td>
</tr>
<tr>
<td>Europe</td>
<td>60%</td>
<td>34%</td>
<td>7%</td>
</tr>
<tr>
<td>Middle East</td>
<td>57%</td>
<td>36%</td>
<td>5%</td>
</tr>
<tr>
<td>Latin America</td>
<td>43%</td>
<td>37%</td>
<td>17%</td>
</tr>
<tr>
<td>Asia/Pacific</td>
<td>37%</td>
<td>47%</td>
<td>13%</td>
</tr>
<tr>
<td>Africa</td>
<td>19%</td>
<td>56%</td>
<td>21%</td>
</tr>
<tr>
<td>GLOBAL MEDIAN</td>
<td>43%</td>
<td>45%</td>
<td>12%</td>
</tr>
</tbody>
</table>

Note: Percentages based on total sample. Russia and Ukraine not included in Europe median.


**2011 Mobile phone ownership among White, Black, and Hispanic U.S. Adults**

<table>
<thead>
<tr>
<th>Group</th>
<th>Smartphone</th>
<th>Other cell phone</th>
<th>No cell phone</th>
</tr>
</thead>
<tbody>
<tr>
<td>White, non-Hispanic</td>
<td>20%</td>
<td>11%</td>
<td>14%</td>
</tr>
<tr>
<td>Black, non-Hispanic</td>
<td>50%</td>
<td>45%</td>
<td>42%</td>
</tr>
<tr>
<td>Hispanic</td>
<td>30%</td>
<td>44%</td>
<td>44%</td>
</tr>
</tbody>
</table>

Source: The Pew Research Center’s Internet & American Life Project, April 26 – May 19, 2011 Spring Tracking Survey. n=2,277 adult internet users ages 18 and older, including 755 cell phone interviews. Interviews were conducted in English and Spanish. “Smartphone ownership” includes those who say their phone is a smartphone, or who describe their phone as running on the Android, BlackBerry, iPhone, Palm or Windows platforms.

“smartphone dependence”
mHealth Intervention to Improve Diabetes Risk Behaviors in India: A Prospective, Parallel Group Cohort Study

Angela Pfammatter, Bonnie Spring, Nalini Saligram, Raj Davé, Arun Gowda, Linelle Blais, Monika Arora, Harish Ranjani, Om Ganda, Donald Hedeker, Sethu Reddy, Sandhya Ramalingam

J Med Internet Res 2016 (Aug 05); 18(8):e207

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View Abstract
Mobile Text Messaging for Health: A Systematic Review of Reviews

Amanda K. Hall,1 Heather Cole-Lewis,2,3 and Jay M. Bernhardt4


The Annual Review of Public Health is online at publhealth.annualreviews.org

Keywords
texting, SMS, short message service, mHealth, cellular phone, cell phone, smartphone, text-messaging interventions

• Efficacy evidence strongest for physical activity, smoking cessation
• Relatively few RCTs
• Support for message tailoring, personalization, variable (daily – weekly) frequency

texts function as prompts/reminders/(education)
Mobile Health Programs
(text, app, wearable, hybrid)

• Kaplan & Stone, *Ann Rev Psych*, 2013 - 21 mHealth RCTs;
  – 6 (29%) show mHealth > control
  – 50% mHealth > control for weight loss at some f/up

• Burke, Ma,..Spring, et al, AHA Behav Change Comm, *Circulation*, 2015 – 38 mHealth RCTs (weight, PA, smoking)
  – 5/8 (63%) U.S. obesity RCTs mHealth > control at some f/up
  – SMS alone ineffective for weight loss
Control Systems Theory* - Rationale for Self-Monitoring as a Behavior Change Mechanism

- Self-regulation requires detection of discrepancy between current state and goal
- People are motivated to reduce the discrepancy

*(Carver & Scheier, 1998)
Same intervention or different?

Tech changes rapidly.
Human behavior change mechanisms remain the same
(or evolve very, very slowly.)

Goal setting
Self-monitoring
Feedback
Incentives
Social support/Accountability

RC1DK087126
Sustaining Self-Monitoring Engagement: Tech + Human

**+Mobile Study** (all new referrals to MOVE!)

- **Record 2 weeks**
  - **Standard:** MOVE group [w/ paper recording]
  - **+Mobile:** MOVE group w/ connected mobile recording

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### Table. Demographic Characteristics of the Study Participants at Randomization

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Connective Mobile Group</th>
<th>Standard Group</th>
<th>Total (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age, mean (SD), y</td>
<td>57.7 (13.5)</td>
<td>57.7 (10.2)</td>
<td>57.7 (11.9)</td>
</tr>
<tr>
<td>Male sex</td>
<td>29 (42.9)</td>
<td>50 (43.4)</td>
<td>59 (85.5)</td>
</tr>
<tr>
<td>Ethnicity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic or Latino</td>
<td>1 (2.9)</td>
<td>3 (8.6)</td>
<td>4 (5.8)</td>
</tr>
<tr>
<td>Not Hispanic or Latino</td>
<td>33 (97.1)</td>
<td>32 (91.4)</td>
<td>60 (94.2)</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>25 (73.6)</td>
<td>27 (77.1)</td>
<td>52 (76.4)</td>
</tr>
<tr>
<td>Black or African American</td>
<td>9 (26.5)</td>
<td>8 (22.9)</td>
<td>17 (24.6)</td>
</tr>
<tr>
<td>College graduate</td>
<td>10 (29.4)</td>
<td>14 (40.0)</td>
<td>24 (37.7)</td>
</tr>
<tr>
<td>Anthropometry, mean (SD)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weight, kg</td>
<td>113.7 (16.1)</td>
<td>110.1 (15.1)</td>
<td>111.1 (15.6)</td>
</tr>
<tr>
<td>BMI</td>
<td>30.9 (5.4)</td>
<td>35.8 (3.6)</td>
<td>33.2 (4.6)</td>
</tr>
<tr>
<td>Waist circumference, cm</td>
<td>120.4 (14.0)</td>
<td>120.4 (8.9)</td>
<td>120.4 (11.7)</td>
</tr>
</tbody>
</table>

Abbreviation: BMI, body mass index (calculated as weight in kilograms divided by height in meters squared).

*Data are presented as number (percentage) of study participants unless otherwise indicated. No between-group differences in baseline variables were observed.

*JAMA Int Med, 2013, 173(2):105-111*
Weight Loss over Time as a function of mHealth Technology access
Treatment Assignment and *MOVE!* Adherence*

*Adherent = Attended >80% of treatment sessions.

Tech alone doesn’t do magic

Tech gives the engaged participant a leg up

So

It's not the tech alone that's doing the work

It's how the tech catalyzes the behavior change mechanisms

How can we learn most efficiently how to get mHealth tech to potently harness behavior change mechanisms?
Social support / social connectedness
The Intervention Challenge

- **Effective treatment** (intensive lifestyle treatment – e.g., DPP, Look AHEAD) produces 7% sustained weight loss and metabolic improvement but **burdensome** (16-36 sessions) and **costly** ($1800/patient)

Provision of human support is expensive

Diabetes Prevention Program, *Diabetes Care*, 2012
27,382 members:

- **89% isolated (no online friends)**
- **11% (N=1,935) did make friends**
  - 26% in isolated clusters of 2-5
  - 64% in giant component

I am traveling to the NIH mHealth Training Institute at UCLA will be back in the office on 8/14/17. For questions please contact Alejandra Senior-Povedano at alejandra.povedano@northwestern.edu.
Treatment Package Approach: The ENGAGED Trial
Reduce DPP treatment intensity by half; reconfigure support components to increase efficiency
3 treatments: 1. self-guided DVD; 2. in-person, paper/pencil; 3. in-person tech

Package Components

- Skills, self-monitoring, group weight loss incentives (peer support)
- 8 in-person group treatment sessions
- Telephone coaching
- Technology (app, accelerometer, texts, message board, peer adherence info)

Message Board
“Happy Birthday, Philly!
May you eat well, but stay within the Fan Meter safe zone...😊”

Spring et al (2017) Obesity
Weight Change (% of Baseline body weight) at 3, 6, and 12 Months

Bars reflect +/- 1 Standard Error

Per cent weight loss

Baseline 3 months 6 months 12 mos

- Standard
- Technology-Supported
- Self-Guided

n.s. ** *
What don’t we know at end of RCT?

<table>
<thead>
<tr>
<th>If Treatment &gt; Control</th>
<th>If Treatment &lt; Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Which components are making positive contribution</td>
<td>• Whether any components are worth retaining</td>
</tr>
<tr>
<td>• Whether all components are needed</td>
<td>• Whether one component had a negative effect that offset a positive effect</td>
</tr>
<tr>
<td>• Which components’ contribution to effect offsets its cost</td>
<td>• Explicitly what went wrong and how to do it better next time</td>
</tr>
<tr>
<td>• How to make intervention more effective</td>
<td></td>
</tr>
</tbody>
</table>
Intervention Optimization Research

Kitchen Sink → Optimized Intervention

1. MOST - active, optimized components – best one size fits most
2. SMART – response heterogeneity, best strategy for adapting to non-response
3. JITAI - individualized just in time adaptive intervention
Opt-In Study – Multiphase Optimization Strategy (MOST) Factorial Design

Optimization of Remotely Delivered Intensive Lifestyle Treatment for Obesity

Principal Investigators
Bonnie Spring, Ph.D. (Northwestern University)
Linda Collins, Ph.D (Pennsylvania State University)

Funded by the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK R01 DK097364)
Primary Aim 1A

Identify which components/component levels, contribute most to

a) average weight loss
b) percent achieving ≥ 7 % weight loss
among overweight and obese adults over a 6-month period.

**Five components**

1. Coaching Intensity
   • 12 v. 24 phone sessions
2. Training participants’ self selected buddies to be supportive
   • No v. Yes
3. Text Messaging
   • No v. Yes
4. Progress Reports to PCP
   • No v. Yes
5. Recommendations to use meal replacements
   • No v. Yes

Examine effect size & cost/component to assemble treatment package producing maximal weight loss attainable for $500
The 5 Steps of Evidence-Based Practice

1. Ask
2. Acquire
3. Appraise
4. Analyze & Adjust
5. Apply

Client/Community Assessment

(�valuation, Dissemination, & Follow-up)
Sequential Multiphase Adaptive Randomized Intervention (SMART)
SMART: Sequential Multi-Phase Adaptive Randomized Trial

SMART Weight Loss Management

Principal Investigators
Bonnie Spring, Ph.D. (Northwestern University)
Inbal (Billie) Nahum-Shani, Ph.D (University of Michigan)

Funded by the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK R01 DK108678)
SMART Rationale

• Population level health management: resources limited, insufficient to meet demand, provide what’s evidence-based and needed – not less, not more (Archibald Cochrane)

• But not yet at precision med: don’t know who needs what, how much, when.. so mimic and systematize what clinicians do in real world: if treatment isn’t working, try something different and learn!!

• What’s being adapted to is treatment non-response (aka stepped care)

• Adaptive: tests an algorithm (if...then) rather than a fixed treatment like what we’ve typically tested in behavioral RCT
SMART Develops Decision Rules for Sequential Treatments that Adapt Respond to Treatment Nonresponse. Treatment = algorithm

SMART Weight Loss Management Primary Aims: Treatment Sequence

• Is the **optimal first line treatment** for a population of overweight and obese adults mHealth alone (App) or mHealth plus coaching (App + C)
  – H1: Those who receive the App alone as a first line treatment will achieve greater weight loss by 6 months compared to those initially assigned to (App + C)
    • [How long to evaluate?] [What’s nonresponse?]

• Is the **optimal response to early weight loss treatment failure** to modestly step-up (add another mHealth component; text messages) or vigorously step-up (add another mHealth component plus a traditional component; coaching or meal replacement)
  • [How to step down after response?]
Randomization Scheme

**EQUIPOISE INDUCTION**

First randomization will occur at baseline.

- **App**
  - **NON-RESPONSE**
    - Non-response status will be assessed at weeks 2, 4, and 8.
    - Randomize
      - Vigorously Step Up App + T + C
        - [A]
      - Modestly Step Up App + T
        - [B]
  - **RESPONSE**
    - Participants will be classified as responders so long as they do not meet criteria for non-response.
    - Continue** App
      - [C]
  - **NON-RESPONSE**
    - Non-response status will be assessed at weeks 2, 4, and 8.
    - Randomize
      - Vigorously Step Up App + C + T + MR
        - [D]
      - Modestly Step Up App + C + T
        - [E]
  - **RESPONSE**
    - Participants will be classified as responders so long as they do not meet criteria for non-response.
    - Continue** App + C
      - [F]

Follow-up Assessments will occur at months 3, 6, and 12.

*A non-response will be re-randomized to one of the two augmentation tactics as soon as s/he is classified as a non-responder (either at week 2, 4, or 8) and will receive the assigned augmentation tactic until week 12.*

**Responders will continue with the assigned initial treatment until week 12.**
Just in time Adaptive Intervention (JITAI)
MD2K Smoking Study Team

Northwestern Medicine

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Gwen Ledford

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UNIVERSITY OF MICHIGAN

Inbal (Billie) Nahum-Shani

Susan Murphy

RICE

Mustafa Al’Absi

Dave Wetter

The University of Memphis

Santosh Kumar
JITAI – Just in time adaptive intervention

• Adaptation to patient states that change rapidly in real time

• What’s being adapted to is patient’s changing states of:
  – Vulnerability, risk
  – Opportunity, receptivity to intervention

• Continuous digital data gives us opportunity to sense and anticipate need/receptivity
The Problem

• Most (93%) unaided smoking cessation attempts fail in 1st week
  ➢ 95% of lapses (slips, few puffs) followed by relapses
  ➢ We encourage patients to call when tempted to smoke. ...but they rarely do

• Stress predicts lapse/relapse=> increasing state of risk?
  ➢ Evidence based stress reduction treatments exist
  ➢ Is stress a useful tailoring variable for decision rule for WHEN to trigger intervention?

WE DON’T KNOW.....

Sense2stop study will figure out
Two Alternative Hypotheses

• Prompt relaxation during stress (heightened state of relapse risk):
  ▪ Pre-empt, manage the stress episode
  ▪ Contain rising state of relapse risk

• Prompt relaxation during no-stress (heightened state of receptivity to intervention)
  ▪ Stress → limited cognitive capacity to pay attention and learn
  ▪ No stress → State of opportunity to master, practice relaxation skills

▪ Null: prompt under stress or no stress - no difference
Sensors, Detection Algorithms

- **Puffmarker** Detect smoking puffs, validated against EMA, camera
- **cStress** classifies every minute as Stress / Not Stress, validated against cold pressor, public speaking, PASAT

EMI prompt linked to stress detection

Ground Truth

Smoking detection

Real time stress detection
JITAI Outcomes: How to tell if the intervention is working?

- **Proximal outcome**: short-term goal the intervention is intended to achieve, MEDIATOR ON CAUSAL PATH TO DISTAL OUTCOME
  - Reduce probability/increase time to next stress episode
  - Reduce probability/increase time to a lapse

- **Distal outcome**: ultimate goal the intervention is intended to achieve
  - Reduced probability/increased time to smoking relapse
  - To be examined when JITAI algorithm is tested in an RCT
  - E.g., if available (not driving, not prompted in last hour, good data quality) and stressed, then EMI.
  - If not available or not stressed, do nothing.
Conclusions

1. Technology supported interventions enable us to expand the reach, reduce the burden, refine the tailoring of behavioral interventions.

2. Although technology evolves rapidly, many of the catalytic behavior change mechanisms harnessed by mHealth interventions remain unchanged.

3. Though mHealth tech can be very engaging, it rarely changes behavior in and of itself. Rather, it affords new, compelling sensing and delivery channels for behavior change interventions.
Conclusions

• New technologies and research designs can improve how efficiently we optimize interventions
  
  – create optimally efficient and effective interventions for the average person (MOST designs)
  
  – Develop stepped care decision rules to address between person heterogeneity in treatment response. What should be tried first? For how long? What should be tried next? What should be the protocol for weaning people off treatment? (SMART designs)
  
  – Develop tailoring rules that specify when and how to address changing states of risk and receptivity to intervention (JITAI designs)
  
• As more technologies become available adapting to receptivity (managing burden) may well become even more critical than adapting to risk
Thank you!

- NIH
  - R01DK108678 (Spring)
  - R01DK097364 (Spring)
  - T32CA193193 (Spring)
- AHA
  - 14SFRN20740001 (Spring)
- NIH
  - NCI RLCCC (Platanias)
  - U54EB020404 (Kumar)
  - UL1TR001422 (Lloyd-Jones)

Our Team

(Left to right) Gleb Iakovlev, David Conroy, PhD, Miriam Davidson, MScS, Angela Pfammatter, PhD, Jennifer Warnick, Ginne Meyers, Gene McFadden, Steven Driver, MD, MPH, Bonnie Spring, PhD, Elyse Daly, Tiara Adams, RD, LDN, Christine Pellegrini, PhD, Sara Hoffman, Claire Maby, Jeremy Steglitz, MPH, MS, Elena Garza

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