Healthful Connected Living: Vision and Challenges for the Case of Obesity

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Abstract—
We envision a new integrated suite of multimodal sensing and artificial intelligence techniques that can incorporate advances in health psychology to produce effective solutions for long-term healthful living. We discuss challenges and opportunities arising in realizing this vision.

1. Introduction

Healthful living involves not occasional contact between a person and a health provider but *constant attention* to health and persistent healthful behaviors. It largely succeeds or fails with respect to chronic conditions. We focus on *obesity*, a serious public health concern whose prevalence is rising. The Centers for Disease Control and Prevention (CDC) reported that in March 2020 42% of US adults could be classified as obese (https://stacks.cdc.gov/view/cdc/106273). The obesity epidemic has serious negative effects, including a rise in Type II diabetes and preventable death; it inflicts an annual medical care cost of $147 billion in the US. At an individual level, obesity affects one's engagement in physical and social activities and can be difficult to get out of. To address obesity, users must constantly be on their guard against lapses into unhealthy behaviors.

Our envisioned solution, *DyaLog*, addresses healthful living via three interwoven research advances. **Low-power sensors** with power vs. accuracy and other tradeoffs controlled by AI. **User modeling** to model a user's behavior and health for providing dynamically personalized interventions. **Social context modeling** to enhance and apply existing psychological techniques for healthful interventions.

The problem is challenging but within reach of current technology. First, health psychology explains how people may be motivated to achieve their goals through *nudges* toward a *growth mindset* [1], which encourages sustained motivation and adaptive self-regulatory responses in the face of obstacles. Second, multimodal sensor platforms that support physico, chemo, and mechano capabilities to jointly capture user data are now possible. Small, ultra-low-power sensors can be employed unobtrusively in long-running monitoring of a user's context, activity, and physiological state. Third, AI enables intelligent agents that model a user's context, produce interventions adaptively, and continually learn from how a user responds.

2. Scenario

Imagine a DyaLog user, Alice, who wears the DyaLog device linked to an agent on her phone, to which it continually sends data. With the device being small, *self-powered*, and never having to be taken off, Alice could almost forget that she is wearing it. Through sensors of the device and the phone (e.g., ambient sound, location, app usage), Alice's agent creates a *user model* of her and detects her *social context*. Her model incorporates her changing physiological state (e.g., heart rate) and her baseline health (e.g., heart rate variation over a day). Alice's agent would initialize (and revise) its model based on a short questionnaire detailing her feelings and goals (e.g., the amount of exercise she will do daily and weekly). The social context includes whom Alice is interacting with, in what activity, and how she may align her behavior to that of her companions.

Alice's DyaLog agent thus doesn't begin tabula rasa. It learns explicit biomarkers such as her heart rate and implicit concepts composed from attributes of her environment. It learns how well Alice progresses toward her health goals in changing circumstances. The agent intervenes via gentle *nudges*, such as telling Alice of her recent exercise success, showing her data about her health rate, explaining how her goals remain within her reach, and so on.

3. Sidebar: Psychology

Bandura [2] introduced self-efficacy as a key element in behavior change: in simple terms, to have a shot at success, people must believe they can succeed.

An individual's *mindset* is a belief system regarding the malleability of personal attributes [1]. People's mindsets—their beliefs about the stability of an attribute—guide how they think, feel, and act. A belief that personal traits (e.g., intelligence, athletic ability, weight) are fixed is called a *fixed mindset*, and a belief that traits can be improved is called a *growth mindset*. When they face obstacles and setbacks, as inevitably happens in working toward long-term goals such as weight loss, people with growth mindsets believe they can recover—and adaptively self-regulate to work toward their goal [1].

Briefly, a person with a growth mindset believes that body weight and health are something they can improve with effort and hard work, whereas a person with a fixed mindset does not. Importantly, a mindset can be taught and can help individuals overcome inevitable challenges to their weight, health, nutritional, and exercise goals through effective self-regulation.

Burnette and Finkel [3] evaluated the effect of mindset and knowledge messages on weight gain. Most participants in the no-treatment and knowledge intervention groups gained weight, as in other studies of dieting. However, participants who received growth mindset messages adopted beliefs in their weight being controllable, which buffered against dieting setbacks—and they recovered to continue to lose weight.

An *adaptive intervention* is dependent upon some observable attribute of a human's behavior or environment. Nahum-Shani et al. [4] provide a conceptual framework for just-in-time interventions for health. Adaptive interventions are expressed as IF–THEN decision rules in which the conditions are based on directly observed, low-level attributes, e.g., heart rate being above or below a preset threshold. These decision rules are prespecified. However, decision boundaries are generally not easy to capture at scale, and such rules become unwieldy if made adaptive to context.

4. Sidebar: Sensing for Obesity

Studies have shown that obesity is a complex problem not simply the consequence of overeating and low physical activity. Key factors include (i) baseline health, such as heart rate variability and metabolic rates, (ii) (psychosocial) stress, (ii) physical exercise, and (iv) food intake. No single sensor can measure these accurately and precisely. What is called for is multimodal (physico/mechano/chemo) sensing that enables data from different modalities to be correlated and converted to desired metrics.

Baseline health refers to a user's overall health; it comprises baseline heart rate, heart rate variability, sleep, and metabolic rate. Obese individuals have higher respiratory rates and lower tidal volume, as obesity causes compression of the diaphragm, lungs, and chest cavity, and have higher heart rates (HR) and heart rate variability (HRV). Further, excess fat reduces respiratory muscle strength.
Psychosocial stressors: Obese individuals ex-

perience stigma, depression, low self-esteem, and anxiety. Galvanic skin response (GSR) measures autonomic nervous responses to stress, other psycho-physiological stimuli, and respiration rates. An increased stress (endocrine) response results from sympathetic nervous activity, which can be monitored via GSR and HRV to assess the effect of personal social status. Also, speech is an indicator of social interaction.

Physical activity is measured directly via HR, HRV, and accelerometer readings. Blood lactate accumulates faster during incremental exercise in obese animals and correlates with decreased exercise performance. Lactate changes due to obesity appear measurable in sweat [5].

Food intake can be tracked through jaw and larynx sensors and images (to identify what is being eaten). Sensing swallowing frequency and duration is potentially unintrusive yet precise.

These obesity metrics correlate in subtle ways. Whereas cardiovascular disease (CVD) in obese individuals is affected by baseline HRV, regular exercise can offset the negative effect of obesity on HRV. Gutin et al. [6] show that HRV increased over four months when obese children were engaged in physical training and declined when they stopped training. Moreover, HRV is reduced in obese subjects, indicating depression in parasympathetic activity. Frequency domain analysis of HRV shows a depression in sympathetic activity—i.e., obesity presents an autonomic function disturbance in both parasympathetic and sympathetic activity. Psychosocial stress moderates these factors. Night eating can impair sleep and result in weight gain. Research suggests that eating patterns, body temperature, and indirect measures of sleep [7] can inform behavior interventions.

5. Envisioned Solution

As Figure 1 shows, we imagine a wearable device coupled with an AI agent. The device is low-powered; most computation, communication, storage, and user interaction reside on the phone where the AI agent lives. The agent continually monitors a user's health status, activities, and context to produce interventions optimizing for form and frequency.

Figure 2 shows DyaLog's conceptual model of interventions, mediating variables, intentions, behaviors, and outcomes. The context moderates most influences but is elided for readability. A growth mindset reduces the stress response to health information.

As Figure 3 shows, a few sensors are enough to compute our obesity metrics. We adopt the form factor of a chest patch as it provides access to all the above signals and is easy to use, thus promoting compliance.

For the device, a printed circuit board is housed in a 3D-printed plastic shell (Figure 4). The platform can be built on a self-adhesive, flexible, and highly stretchable polymer to maintain good contact with the skin in daily motions. A device of $\approx$3cm $\times$ 4cm $\times$ 1cm is within reach of current technology.

6. Challenges and Opportunities

We now describe challenges and opportunities in realizing our vision.

6.1. Multimodal Sensors for Obesity

We describe sensing capabilities along with the needed AI control of them to be effective despite low power.

Advances in Sensors

Heat flux can be used to determine the metabolic rate, especially when correlated with motion data provided by accelerometry. Changes in body temperature correlate with metabolic rate changes and the pathophysiology of obesity Landsberg et al. [8]. A thermoelectric generator (TEG) module can accurately measure heat flux coming off the human body as a Seebeck voltage across the device.

GSR's simple circuitry and lack of parasympathetic interference make it a valuable sensor for stress. Monitoring GSR with HR and HRV measures sympathetic nervous activity and may provide an early indication of cardiovascular disease associated with obesity. The essential factor in signal quality is a low-impedance electrode. To achieve long-term monitoring, we need a highly conformal and flexible GSR electrode that avoids signal degradation and increases shelf-life.

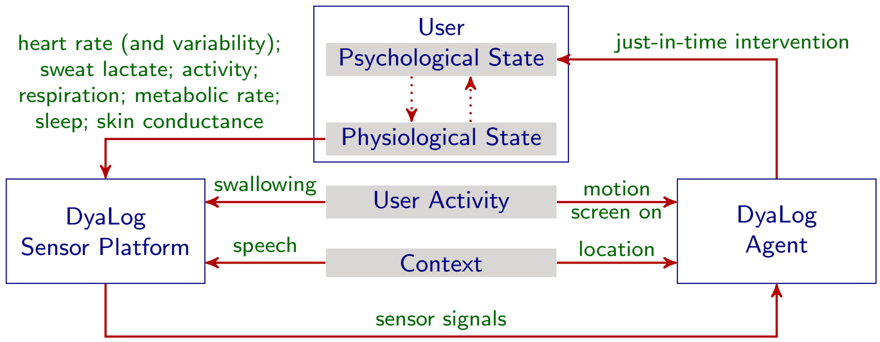

Figure 1. Our research themes, conceptually. DyaLog is conceived of as having two components, a wearable sensor platform and an agent. The user is modeled via interacting psychological and physiological states. The shaded boxes are measured directly or indirectly.

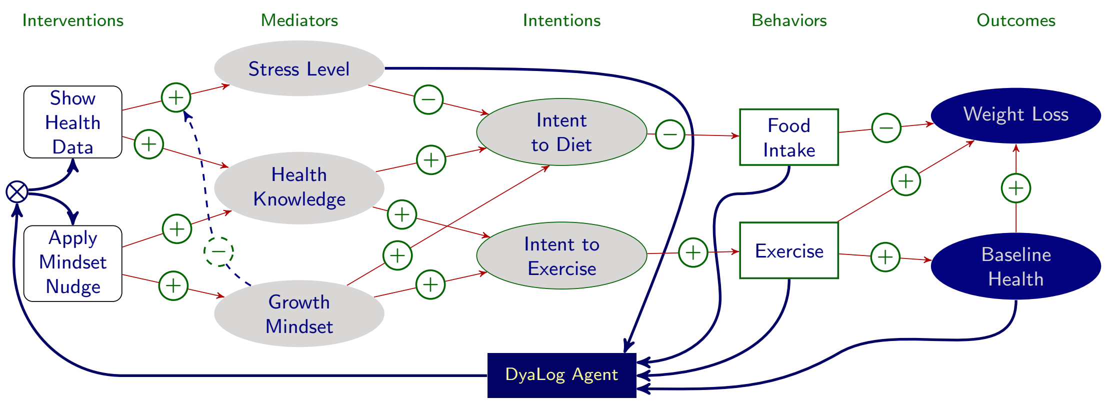

Figure 2. DyaLog's conceptual model. The $+$ and $-$ symbols indicate positive and negative influences, respectively. The DyaLog agent observes the variables to determine which intervention to apply and when.

We need to go beyond current photoplethysmography (PPG) sensors [9] to accommodate obese individuals since tissue components such as melanin and fat affect the absorption of light and require adjustment of PPG wavelength.

Sweat lactate sensing is attractive because it is noninvasive yet correlates well with blood lactate. Physical exercise activates lactate-producing eccrine sweat glands on the chest, indicating improvements in the exercise efficiency of obese individuals.

AI Control of Sensors

A wearable chest platform that supports communications, e.g., through Bluetooth Low Energy, must rely on low-power technologies. The power consumption for some sensors (e.g., PPG) is heavy and depends on the user's personal traits. For example, PPG uses an LED to shine light through the skin and needs additional power for obese or dark-skinned users.

Thus, we need ways to adaptively determine sampling rates to satisfy sensing needs with the lowest power load. An approach might be to adapt power-sensitive active learning where the uncertainty of an inference is traced back to different sensors and the least power combination of sensors chosen to gain sufficient certainty.

Challenge 1. Sensor power management

How can we develop and integrate sensors with AI such that the sensors have tunable power profiles and AI techniques optimally control the power profile of a set of sensors depending on the need for information to make a judicious health intervention?

6.2. Context-Adaptive Interventions

Self-regulation means that a user monitor, assess, and regulate their cognitive, affective, metacog-

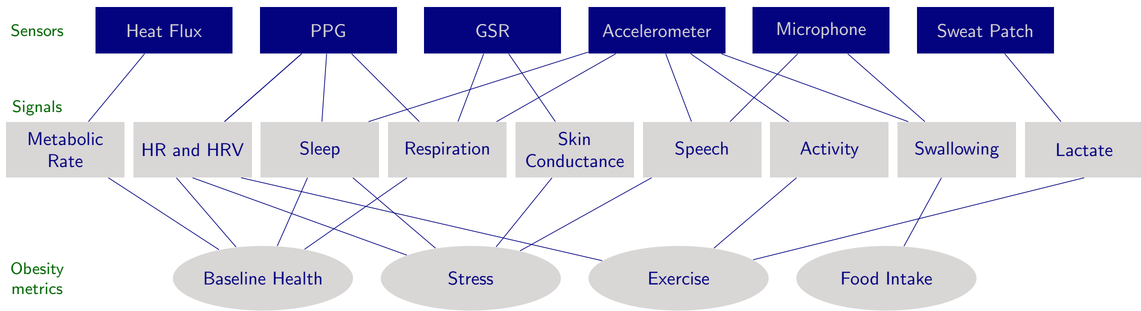

Figure 3. DyaLog's multimodal sensors and signals. The sensors (top row) produce signals (middle row), which contribute to obesity metrics (bottom row). Established sensors can be used in new ways—e.g., a microphone and an accelerometer placed on the chest together can sense swallowing.

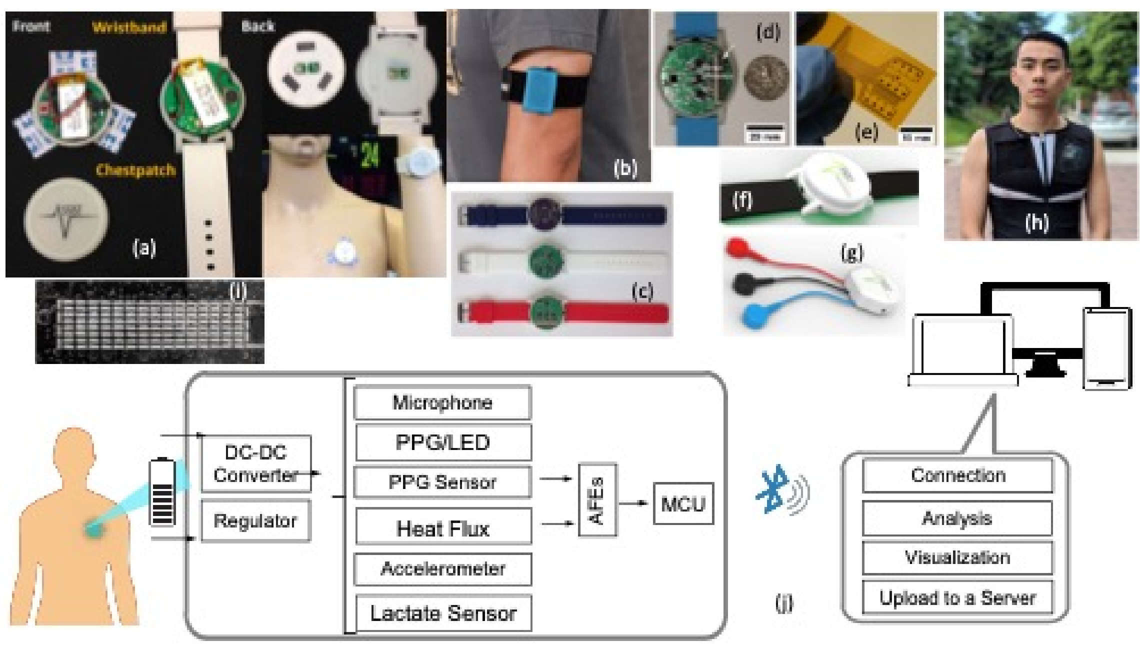

Figure 4. Existing sensor platforms: (a) chest patch and wrist-band containing ECG, PPG, sensors for pulse oximetry, motion, coughing, and wheezing, and undersides of the optical sensors, (b) armband ECG for cardiac monitoring, (c) wristbands for PPG and ozone detection, (d) potentiostat wristwatch with connectors that (e) connect to PDMS sweat collection and sensing, (f) ASSIST health watch, (g) chest ECG with electrodes, (h) self-powered ECG shirt powered by body heat, (i) flexible TEGs modules used for heat flux measurements, and (j) the envisioned DyaLog platform.

nitive, and motivational processes to accomplish health objectives. The user's strategy may be simple (e.g., tracking one's diet and exercise) or cognitively demanding (e.g., seeking an exercise partner or creating a meal plan). Mapping and capturing strategies in real-world settings is difficult due to an explosion of choices, especially across contexts.

Our agents must put the user in charge while helping the user. For example, a user may focus on exercise or diet, and for exercise, choose a time and location. The agent can help the user make the choices that are best for the user and help the user comply with those choices. The agent could help identify if a user has set up unrealistic health goals, especially if it is a repeating concern. The agents could share their users' experiences in a privacy-preserving manner.

Intelligent Nudges

People make many decisions every day, including 200 food-related decisions per day on average [10]. Accordingly, we can model a user's daily activities (of interest) as sequential decision-making under uncertainty. Reinforcement learning (RL) is a popular machine learning paradigm for decision making under uncertainty. An RL agent seeks to induce a policy for choosing an action in any situation that would maximize the cumulative reward.

RL is challenged by delayed rewards since delay complicates attributing an outcome to a specific choice. Health improvements arise over durations of weeks. Thus, tactics such as crash dieting, which give immediate rewards, can be counterproductive. This problem demands methods for long-term temporal credit assignment [11] under noisy data.

Figure 5 shows how the framework relates a user, their agent, and the world. The user's reward function and view of the state are not known to the agent; the actions of relevance are decisions about diet and exercise and are observable. The agent views the state based on readings of the user's physiological state, context, and activity, and the reward as improvements in baseline health. Its decision is whether and how to nudge.

We adopt mixed-initiative decision making to balance giving a user a true feeling of control over their own health and helping them progress toward their goal. The user is the main decision maker, and the agent has a supporting function. When the user makes a suboptimal choice on a critical decision, the agent determines when and how to intervene based on the user model; there is no intervention except for critical decisions.

Different users follow different progression trajectories in healthful living. Since users generally make decisions based on tradeoffs between complex factors, e.g., time, social pressure, and current environment, it is nontrivial to infer a user's intentions—their reported health goals (e.g., target weight and amount of weekly exercise) may not reflect their actual decision making. Modeling users based on heterogeneous trajectories is challenging because of complex context, hidden preferences, and temporal dynamics. But doing so is essential in producing effective nudges that promote good health and a growth mindset.

Challenge 2. Adaptive nudges

How can an agent determine a user's current strategy and produce effective tactical nudges to follow through on a given strategy and strategic nudges to consider alternative strategies?

A possible approach is to adopt *Inverse Reinforcement Learning (IRL)* to produce nudges. Whereas RL assumes a reward function for policy induction, IRL infers a reward function from a set of trajectories to feed into RL. The agent would infer users' strategies based on sensed behaviors and use them in its subsequent reasoning.

Applying the Social Context

Social context influences healthful strategies, such as "have a light lunch since you have a big dinner later" or "take a hike with a friend." Therefore, a challenge is to recognize the social contexts (e.g., friends, family, colleagues, and so on) that influence health-related activities. Not only is companionship crucial for one's mental health, but social talking and eating are also relevant to obesity.

Whereas an agent may be able to proceed standalone to infer its user's context, there are natural limitations to how much it can accomplish based only on its local data. For example, it may be able to infer if the agent is carrying out a conversation at home or is in a crowded place but not tell who the user has gone on a run with. Imagine users link their DyaLog agents with a *buddy*, i.e., a family member or friend. The respective agents can detect each other's proximity via sensors such as Bluetooth Low Energy. The agents share minimal information about their user's activity with a nearby buddy. Thus, they can detect if their user is talking, eating, or walking in the company of a buddy. These can be combined with time to identify or recommend a regular walk schedule with a buddy.

IRL was designed to tackle a *single* strategy, but our users follow diverse strategies. Therefore, a challenge is to federate the agents to learn from each other to help their respective users, incorporating methods such as expectation maximization [12].

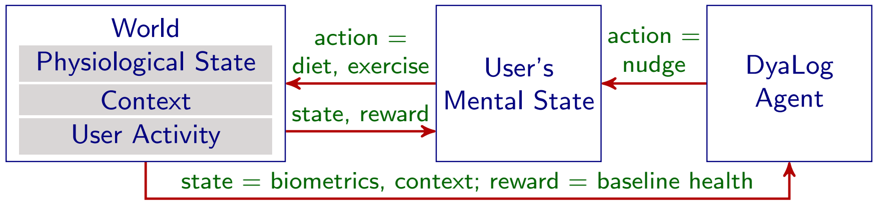

Figure 5. Our reinforcement learning–based framework for nudges.

> **Challenge 3. Incorporating social context**
>
> How can agents cooperate to incorporate social context in their decision making regarding their respective users in a way that respects the privacy of each of the users?

6.3. User Interaction and Evaluation

Although we have framed the above motivation in terms of mindsets for healthful living, it is better understood as a stand-in for any psychological approach. Recognizing that health psychology is a changing field and that current research is mainly conducted in offline settings, it is plausible that previous findings might not hold up in the present use case of real-time sensing and intervention.

Unlike in an offline study, the DyaLog agent may query a user about the user's mindset at random intervals to identify a better sample of their mindset as they lead their life. Specifically, the agent can apply a standard scale including mindset beliefs (e.g., "No matter who you are, you can change your health") and a scale for self-reported setbacks and their severity [13].

Accordingly, we envision DyaLog as an experimental platform to consider alternative approaches from health psychology. Specifically, the agent may provide its user information about their health condition, including biometrics such as heart rate and activity (number of steps walked) along with encouragement to report their health goals and strategies.

Below is an example evaluation we may conduct through DyaLog agents. In the *knowledge condition*, the agent merely provides the information. In the *growth mindset condition*, it provides the information along with advice on the malleable nature of one's health and how to lose weight. The following hypotheses are pertinent to the evaluation of whether real-time interactions via DyaLog conform to traditional interventions.

Stress. With growth mindset interventions, users (1) exhibit lower stress responses to knowledge about their own health performance and (2) report greater engagement in health behaviors than those in the knowledge condition.

Engagement. Individuals in the growth mindset condition will (1) achieve better health outcomes (including weight loss) than those in the knowledge condition, who will (2) achieve better health outcomes (including weight loss) than those in the no-treatment control condition.

Unintrusive metrics based on observable behavior, even if less accurate, are preferable to intrusive ones. Possible ideas include using social engagement and physical exercise as surrogates for (lack of) stress, and user input of weight. Indeed, it's even possible to combine this information with the relevant social contexts to determine the effects of social interaction on, e.g., stress and engagement.

> **Challenge 4. Continual evaluation**
>
> How can we continually improve the health psychology underpinnings of DyaLog, identify new interventions by agents, and personalize these interventions to users?

7. Discussion

Adopting healthful habits is a long-term process. People are liable to lapse from time to time by choosing the wrong diet or skipping exercise. What differentiates success from failure often is being open to learning about one's performance, recognizing one's lapses, trying again after a lapse, and self-regulation to adopt good habits. This simple idea motivates our approach to healthful connected living.

An overarching challenge is of achieving trustworthy AI [14]. DyaLog supports an unobtrusive device along with an intelligent agent that helps a user maintain their health state, learns the user's individual behaviors and social interactions, and provides interventions inspired by health psychology. DyaLog is inherently decentralized and architecturally supports privacy: all user context stays with their agent, which serves the user's interest and avoids relying on a service provider with control over the user's data.

To realize DyaLog in practice presuppose correlated advances in AI and sensors. These advances are plausible but potential challenges include producing low-power and unintrusive sensors that provide accurate measurements of social context and behaviors such as swallowing, user modeling in context with small amounts of data, and continual evaluation. Factors such as usability and the price of the sensors and the software, which are not in our scope, are also clearly relevant.

Acknowledgments

We thank Jeni Burnette for advice on health interventions. We thank the NSF for partial support for this research (MPS: IIS-2116751; MC: IIS-1651909).

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