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Scaffolding the Mastery of Healthy Behaviors with Fittle+ Systems: Evidence-Based Interventions and Theory

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We present a series of mHealth applications and studies pursued as part of the Fittle+ project. This program of research has the dual aims of (1) bringing scalable evidence-based behavior-change interventions to mHealth and evaluating them and (2) developing theoretically based predictive models to better understand the dynamics of the impact of these interventions on achieving behavior-change goals. Our approach in the Fittle+ systems rests on the idea that to master the complex fabric of a new healthy lifestyle, one must weave together a new set of healthy habits that over-ride the old unhealthy habits. To achieve these aims, we have developed a series of mHealth platforms that provide *scaffolding interventions*: Behavior-change techniques and associated mHealth interactions (e.g., SMS reminders; chatbot dialogs; user interface functionality; etc.) that provide additional support to the acquisition and maintenance of healthy habits. We present experimental evidence collected so far for statistically significant improvements in behavior change in eating,

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exercise, and physical activity for the following scaffolding interventions: guided mastery, teaming, self-affirmation, and implementation intentions. We also present predictive computational ACT-R models of daily individual behavior goal success for data collected in guided mastery and implementation intention studies that address goal-striving and habit formation mechanisms.

1. INTRODUCTION

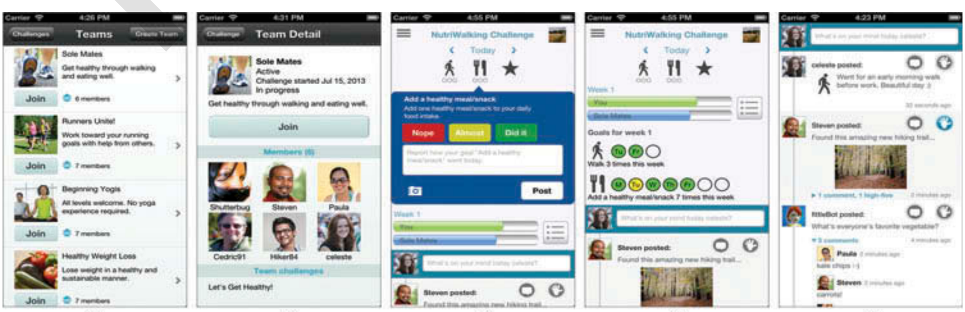
With the recent thrust to develop precision medicine there are opportunities to apply social and behavioral science to the challenges of helping people develop healthier lifestyles that include better diet, increased physical activity, better sleep, and greater resilience to stress, etc. (Riley, Nilsen, Manolio, Masys, & Lauer, 2015). As highlighted in Riley et al. (2015), 70% of healthcare costs are due to changeable behavior (e.g., diet, fitness, smoking), and behavioral and environmental factors account for more deaths than genetics. Mobile health (mHealth) systems including, more generally, pervasive technologies such as the Internet of Things, offer novel ways for supporting people in changing their behavior in the actual ecology of their everyday environments (Heron & Smyth, 2010). A recent comprehensive review of mHealth (Silva, Rodrigues, De La Torre Díez, López-Coronado, & Saleem, 2015) resolved that mHealth services and applications are already playing a very important and determinant role in restructuring the old healthcare services and systems that are still based on the physical relationship between patient and physician. mHealth provides a path for translating evidence-based interventions (EBIs) onto delivery systems that are replicable, scalable, and sustainable, with great economies of scale for healthcare delivery (Rotheram-Borus, Swendeman, & Chorpita, 2012). For the field of human-computer interaction, and the social and behavioral sciences more generally, mHealth also provides new opportunities to develop theory about interventions in the ecology of everyday life, with a focus on meaningful behavior (Baumeister, Vohs, & Funder, 2007; Harari et al., 2016).

In this article, we present a series of mHealth applications and studies pursued as part of the Fittle+ project. This program of research has the dual aims of (1) bringing scalable evidence-based behavior-change interventions to mHealth and evaluating them (Rotheram-Borus et al., 2012) and (2) developing theoretically based predictive models to better understand the dynamics of the impact of these interventions on achieving behavior-change goals (Spruijt-Metz et al., 2015). The empirical studies and predictive models have been presented previously in disparate sources. Here we present, for the first time, the broader unifying concept of *scaffolding interventions*: Behavior-change techniques and associated mHealth interactions (e.g., SMS reminders; chatbot dialogs; user interface functionality; etc.) that provide additional support to the acquisition and maintenance of healthy habits. The general programmatic approach we have pursued involves selecting scaffolding interventions from the evidence base on behavior change techniques, refining these for mobile health delivery, and understanding their dynamic effects on behavior change using computational cognitive models developed in ACT-R (Adaptive Control of Thought-Rational; Anderson, 2007).

1.1. Overview of Fittle Functionality

We use the term Fittle+ for a project that has explored several systems that evolved as variations of the Fittle mobile phone application (Du, Youngblood, & Pirolli, 2014). As background for our studies, it is useful to understand the core functionality of Fittle. Figure 1 shows screen images from that initial Fittle system presented in Du et al. (2014). Users selected for themselves, or were assigned, to multi-week challenge program involving sets of related daily behavior-change goals. A user could start, join, or be assigned to a team (Figure 1a). The primary Fittle screen is the Fittle dashboard (Figure 1c). The Fittle dashboard consists of three parts. The top portion shows the daily behavior-change goal icons with their completion status shown below as a set of circles similar to a horizontal traffic light. Tap-selection of the goal icons (as shown in Figure 1c under the blue-backed area) accesses the title, basic reminder details, substitution tasks, detailed information about the goal in an electronic card (which may include video demonstration, images, detailed instructions, substitution suggestions, background information, external reference links, links to other related Fittle cards, and more), and the ability to self-report completion or submit a multi-media post to the team feed. The middle section of the dashboard in Figure 1c provides visual analytics showing the user's and the team's goal accomplishment this week. The weekly goal set view, as illustrated in Figure 1d, shows the user all of the behavior-change goals that Fittle will schedule the week. The user can interact and share with his or her team (Figure 1e). Users can share information and multi-media (e.g., photos) with the

FIGURE 1. Fittle® Mobile Application(A) Teams Available, (B) the Details of a Team, (C) Activity Information, (D) Overall Goals for This Week, and (E) the Team-Based Social Activity Feed.



team. Users can give high fives to other users in the same team and comment on each other's posts. All the posts, comments, and high fives are public information in the team. Users may also communicate directly with each other through a peer-to-peer messaging system.

2. THEORETICAL BACKGROUND

2.1. From Good Intentions to Healthy Habits

Our approach in the Fittle+ systems rests on the idea that to master the complex fabric of a new healthy lifestyle, one must weave together a new set of healthy habits that over-ride the old unhealthy habits. Fogg (Fogg, 2009; Fogg & Hreha, 2010) has provided useful summaries and practice-oriented methods for decomposing larger lifestyle changes into "tiny habits," (behaviors) to be changed, and for matching target behaviors with solutions for achieving those behaviors. The path to developing healthy habits is a difficult one, and that path typically begins with the adoption of intentions to change, the setting of goals, and repeated striving to achieve those goals (Graybiel, 2008; James, 1890; Wood & Neal, 2007).

2.2. Individual Behavior Change Theory and Interventions

A summary of the current state-of-the-art in behavior change theory and techniques is well beyond the scope of this article. But a recent, multi-year effort to produce such a summary (Michie et al., 2013; Michie, West, Campbell, Brown, & Gainforth, 2014) identified 83 theories, 26 mechanisms of action, 93 behavior change techniques, and 1725 theoretical constructs. A recent meta-analysis (Samdal, Eide, Barth, Williams, & Meland, 2017) of the literature on behavior change techniques identified in Michie et al. (2014) summarizes the evidence on which techniques produce reliable effects along with effect size estimates. As discussed below, our Fittle systems have incorporated five of the nine behavior change techniques associated with long-term behavior change in diet and physical activity found in Samdal et al. (2017; Table 3), as well as implementation intentions and self-affirmation techniques that also have robust effects (Cohen & Sherman, 2014; Epton, Harris, Kane, Van Koningsbruggen, & Sheeran, 2015; Gollwitzer & Sheeran, 2006).

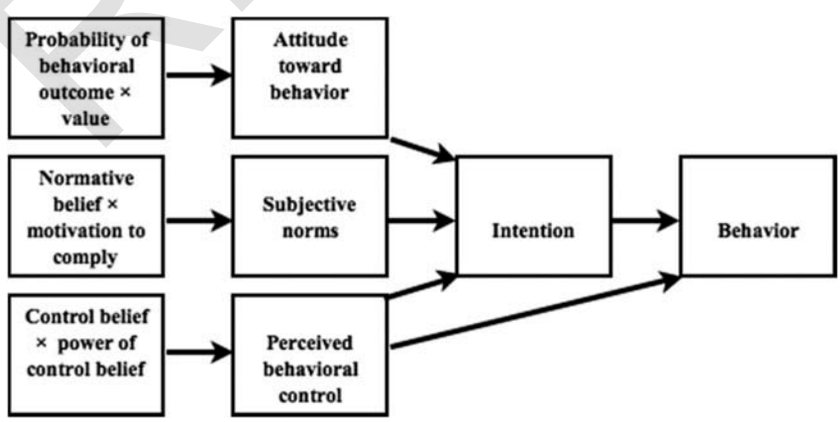
Individual-level health behavior theories (Brewer & Rimer, 2008) include the Transtheoretical Model (Bridle et al., 2005), the Health Belief Model (Harrison, Mullen, & Green, 1992), Goal Setting Theory (Locke & Latham, 2002), and the Theory of Planned Behavior (TPB) (Ajzen, 1991, 1998). Applied techniques, such as altering the environment (Fogg, 2009; Fogg & Hreha, 2010; Sallis & Glanz, 2009; Wansink & Sobal, 2007) to no longer trigger old unhealthy habits or trigger healthier habits, or psychological therapies such as Motivational Interviewing (Miller & Rollnick, 2013) and Cognitive Behavioral Therapy (Cooper, Fairburn, & Hawker, 2003) build upon these theoretical foundations. None of these theories is specified as the kind of fine-grained predictive and dynamic model of behavior and intervention effects that is necessary for engineering mHealth applications (Riley et al., 2011).

As a theoretical blueprint for supporting the goal-striving phase of habit formation in Fittle+ applications, we were guided by the TPB (Ajzen, 1991). TPB has been studied extensively (Brewer & Rimer, 2008) and meta-analyses support the efficacy of the approach in predicting behavior at a coarse-grained level (Armitage & Conner, 2001). Meta-analyses also suggest that TPB is credited more often in successful Internet-based health interventions than other theoretical models (Webb, Joseph, Yardley, & Michie, 2010). The TPB (Figure 2) proposes that the predictors of a person engaging in a target behavior include the person's intention to do the desired behavior and their perceived control over the behavior—whether the person perceives themselves as being in control of doing the target behavior. In turn, the predictors of intention are attitudes, subjective norms, and (again) perceived behavioral control. Attitudes are whether a person is in favor of doing the behavior. Subjective norms are how much the person perceives social pressure to do the behavior. Attitudes, subjective norms, and perceived behavioral control are all forms of expectancy-value judgments deriving from beliefs about outcomes, significant referents, and specific facilitating/inhibiting factors, respectively.

2.3. Scaffolding Interventions

We propose the concept of *scaffolding interventions*: Behavior-change techniques (e.g., Michie et al., 2013) and associated mHealth interactions (e.g., SMS reminders; chatbot dialogs; user interface functionality; etc.) that provide additional support to the acquisition and maintenance of healthy habits. The Fittle+ systems have core challenge programs containing daily goals that form a backbone of the Fittle + mHealth process, and the scaffolding interventions provide additional supports

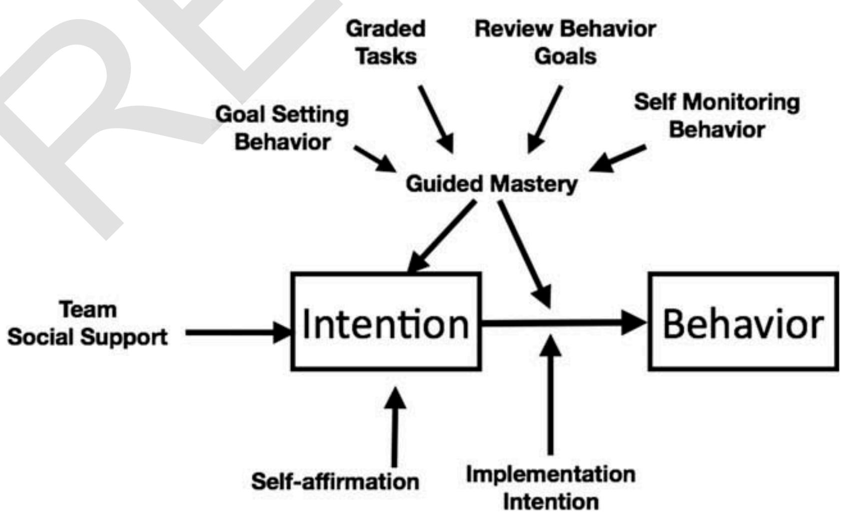
FIGURE 2. The Theory of Planned Behavior.



to that core. The term scaffolding is appropriated from the learning sciences, where it is used to describe support techniques used during the learning process that are tailored to the needs of individual students with the intention of helping the student achieve their learning goals in the context of performance (Reiser & Tabak, 2014). In the learning sciences, scaffolding has been defined as "software tools… that enable students to deal with more complex content and skill demands than they could otherwise handle" (Reiser, 2004, p. 273) with the intent "that the support not only assists learners in accomplishing tasks but also enables them to learn from the experience" (Reiser, 2004, p. 275). Analogously, the Fittle+ systems provide scaffolding to support the building and strengthening of healthy habits by providing a platform for intervention content, methods, and tools that are delivered in the context of the complex ecology of everyday life. The notion of scaffolding is also related to the concepts of shaping, fading, and chaining in classic behavior modification (Martin & Pear, 2016).

Although our studies have typically focused on experimental studies of just a few scaffolding interventions at a time—in order to better understand them—we believe the ultimate platform will have a smorgasbord of scaffolding interventions from which to select and tailor to each individual for maximum support and impact. The meta-analysis in Samdal et al. (2017) of behavior change techniques indicates that including more behavior-change techniques is more likely to produce larger changes in physical activity and diet in both the short term (<12 weeks) and long term (≥12 weeks). Figure 3 summarizes the scaffolding interventions explored in Fittle+ . Guided mastery, teaming, and self-affirmation interventions are all targeted at strengthening behavior-change intentions. Implementation intentions (in addition

FIGURE 3. Interventions Studied in the Fittle+ Project.



to guided mastery) are targeted at translating intentions into actual behavior. The interventions chosen so far for exploration in the Fittle+ project were selected based on bodies of evidence supporting their efficacy, and to provide a set of interventions that targeted increasing intention-to-change as well as that translation of intentions into behavior.

In our studies, we explored (Figure 3) guided mastery, teaming, self-affirmation, and implementation intentions. For reference, the scaffolding interventions we studied are mapped on to the Michie et al. (2013) Behavior Change Taxonomy in Figure 4. The meta-analysis in Samdal et al. (Table 3, 2017) suggests that BCTs 1.1 Goal-setting behavior, BCT 8.7 Graded tasks, BCT 1.5 Review behavior goals, BCT 2.3 Self-monitoring, and BCT 3.1 Social support, have significant effects on long-term outcomes. Meta-analysis (Epton et al., 2015) also suggests that self-affirmations (BCT 13.4 Valued self-identity) have small but reliable effects on intentions and behavior . The meta-analysis of Gollwitzer and Sheeran (2006) suggests medium to large effects of implementation intentions (BCT 1.4 Action planning).

2.4. A Brief History of Fittle+ Systems

Like many software-based research projects spanning many years, Fittle has grown through many interations and side projects. Fittle began in 2012 as "nudg" and for many years we referred to the core platform as the "Nudg Platform" in many publications and patents. The initial struggle was between implementation of the mobile app portion in the emerging HTML5 hybrid methodology or going with a native experience either on iOS or Android, but eventually both. In those early

FIGURE 4. Scaffolding Interventions and Their Mapping to the Behavior Change Taxonomy.

Scaffolding Intervention	Behavior Change Taxonomy	Fittle+ System
Guided mastery	BCT 1.1 Goal-setting behavior BCT 8.7 Graded tasks BCT 1.5 Review behavior goals BCT 2.3 Self-monitoring BCT 2.2 Feedback on behavior	DStress Fittle
Team social support	BCT 3.1 Social support	Fittle
Self-affirmation	BCT 13.4 Valued self-identity	PARC Coach
Implementation intention	BCT 1.4 Action planning	PARC Coach

days, the native experience won out and the largely more popular iOS on the iPhone resonated more with our target population.

The first app instance of Fittle was indeed a version of *nudg* written in native Objective-C for iOS on iPhone and is shown in Figure 5. The backend server system was developed with Django (initially version 1.4) as a RESTful service. This version focused on one exercise and one nutrition goal weekly. It included the social aspect, which has always been core to Fittle. The social aspect in testing proved to be what drove repeated use of the app, but the limited behavior tasks were not compelling, nor did they push the user to improve over time. It was precisely this feedback that led to an offshoot, called DStress, to explore programs of behavior change-inducing activities that progress and adapt.

DStress, was developed as an HTML5 application delivered on mobile devices. That work and our experiences with *nudg* led to adopting health and wellness programs of many varieties that often incorporated both exercise and nutrition.

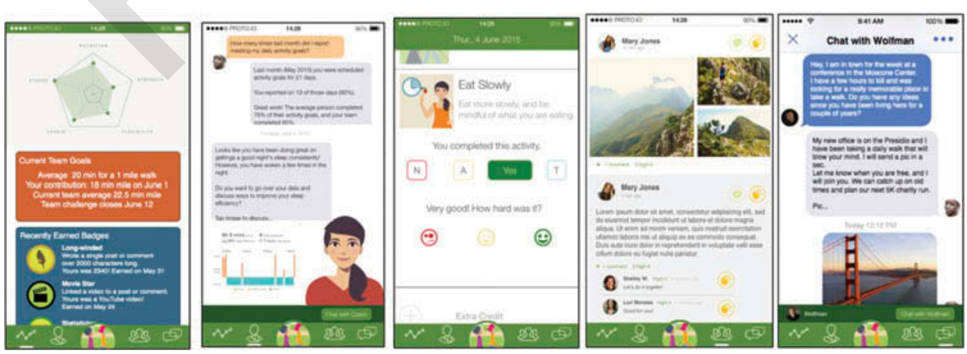
FIGURE 5. The First Versions of Fittle Were Called Nudg and Featured One Exercise and One Nutrition Goal Each Week.

These were offered in a new native iOS app adopting the name Fittle in 2013 with the interfaces shown in Figure 1.

That core Fittle version was adapted, expanded, and used for most of the experiments discussed in this article, including an exploration of the use of the Fittlebot virtual coach (Lukin, Youngblood, Du, & Walker, 2014). An Android version was developed in 2014. The platform and commercial use of the name Fittle® were transferred to internal wellness program divisions of Xerox in 2015, which eventually separated as Conduent, Inc. in 2017. Those versions were used to deliver health and wellness programs over mobile, and eventually the ideas were incorporated in other products at various levels. PARC and our research colleagues continued to use that platform until late 2016, sometimes under specific program names such as *Nutriwalking* (a wellness program that incorporated better nutrition with a walking-based exercise program), when the accumulation of technical debt finally made maintaining and adapting it too difficult for our small research team. As described in this article, research accomplished with this platform covered the social aspects of teams, self-affirmation, dynamic and adaptive user-centric activities, and coaching with over a thousand different users.

In mid 2016, we decided a new research version of Fittle was to be created that could support more adaptive activity programs and personalized, just-in-time adaptive interventions and coaching. The target app design is shown in Figure 6. Being multi-platform with a small engineering/research team led to adopting the latest HTML5 hybrid systems with a React-based (https://reactjs.org/) front-end and Meteor (https://www.meteor.com/) back-end. Essentially, JavaScript everywhere. This provides a consistent experience everywhere, is easier to maintain, and easier to adapt and integrate with other services. Early versions of this software were used in the self-affirmation studies discussed below with the core coaching interaction engine. Because of this initial focus, this new platform was often called the *PARC Coach*. The first full versions of this new platform started use in 2017 with two primary variations: one targeted for an elderly population and one for research

FIGURE 6. The 2016 Re-Design for the New Fittle Built with HTML5 Technologies.



partners in Hawaii. Experiments planned for the next few years are using these versions. In April 2018, PARC released the new Fittle platform code publicly for free research use on Github (https://github.com/PARC/fittle).

2.5. ACT-R Models of Scaffolding Intervention Effects on Healthy Habits

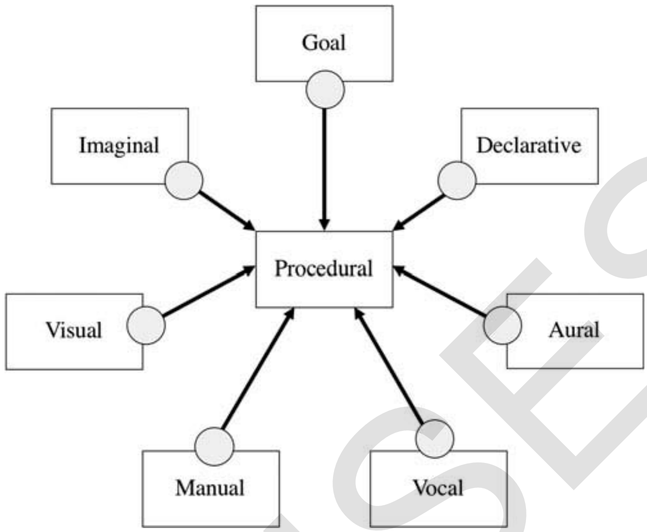
Although the TPB has provided a framework for the Fittle+ selection of mHealth interventions (i.e., self-affirmation, implementation intentions, guided mastery, teaming), we rely on recent neurocognitive theory and models to provide a deeper, more precise, and more dynamical psychological understanding of the effects of scaffolding interventions on behavior change and habit formation. This is because TPB is not specified as a theory capable of addressing the finer-grained, dynamical changes in behavior responsive to repeated interactions with rich, mixed, content, and interactions over many days and weeks. Finer-grained, dynamical models are needed if we want to understand the richer traces of moment-by-moment or daily behavior changes that can now be traced using pervasive technology (Spruijt-Metz et al., 2015). We have used the ACT-R theory (Anderson, 2007) to begin to refine macro-theories such as the TPB (Ajzen, 1991), Social Cognitive Theory (Bandura, 1998), and implementation intentions (Gollwitzer, 1999).

Habits are only gradually learned through the association of specific behaviors to triggering cues in the environment. Triggering cues can include features of physical settings (including cues produced by digital means, such as reminders) and previous actions. A long history of psychological research suggests that there are dual systems involved in habit acquisition and strengthening (Graybiel, 2008; James, 1890; Wood & Neal, 2007). First, a deliberative or controlled goal-striving process motivates and guides seminal attempts at behavior in the relevant contexts. Second, habit learning and strengthening processes form new habits through repeated practice, and habitual behaviors are executed without effortful, controlled, goal striving. Habit formation typically depends on a long period of goal-mediated, consciously controlled, exploration, repetition, and practice of behavior (System 2; Kahneman, 2011), but well-practiced habits appear to be performed automatically without mediating goals, motivation, or deliberative thought (System 1; Kahneman, 2011).

The ACT-R theory (Anderson, 2007) provides a deeper understanding of the dual-system framework for habit formation. We have used ACT-R to develop refined predictive computational models of our interventions for self-efficacy and implementation intentions. ACT-R (Anderson, 2007; Anderson et al., 2004) is a unified theory of how the structure and dynamics of the brain give rise to the functioning of the mind. The ACT-R simulation environment is a computational architecture that supports the development of models.

ACT-R (Figure 7) is composed of *modules* processing different kinds of content. Recent summaries of the theory can be found in Anderson (2007) and the ACT-R web site (http://act-r.psy.cmu.edu). Each ACT-R module is devoted to processing a

FIGURE 7. The ACT-R Theory of Cognitive Architecture. Modules (rectangles) process different kinds of content. Modules are associated with buffers (shaded circles) in which they access and deposit information. The central production module coordinates activities across modules via those buffers.



particular kind of information. Each module is associated with a *buffer*, each module accesses and deposits information via those buffers, and the processing of information across modules and the execution of behavior is coordinated through a centralized *production module*. The production module can only respond to the contents of the buffers.

Important to our models are the modules that process goals and declarative memory. The ACT-R *goal buffer* keeps track of the active goals (when behaviors are being executed). An ACTR *declarative memory module* and its associated *retrieval buffer* model the retrieval of knowledge and past experiences from long-term declarative memory. The declarative module is where goal-striving intentions are stored (before they become active goals in the goal buffer), where memories of past goal-striving experiences are stored, and where implementation intentions are stored. As summarized below, learning and recall mechanisms associated with declarative memory are crucial to predicting the impact of past goal-striving experience on self-efficacy, which in turn affects intentional effort, and ultimately behavior change. Declarative memory mechanisms are also implicated in the effects of reminders on implementation intentions and their effects on goal-striving success. Memory activation mechanisms determine the retrieval of past experiences in current contexts, and base-level learning mechanisms determine how practice and forgetting affect the levels of memory activation.

ACT-R learning mechanisms associated with the production module are central to the acquisition and strengthening of new habits. Important to the ACT-R model of habit formation is the mechanism of *production compilation* (Anderson, 2007; Dayan, 2009; Taatgen, 2004), by which new habits (technically: *production rules*) are acquired. The mechanism works to create new habits that eliminate internal cognitive processing, such as the need to retrieve information from the declarative module or set and maintain sequences of goals. ACT-R utility learning is a variety of reinforcement learning similar to temporal-difference learning (Sutton & Barto, 1998) and Rescorla-Wagner learning (Rescorla & Wagner, 1972). The utility of a new habit is gradually adjusted until it matches the average reward. Through this gradual effect of reinforcement learning, a new habitual behavior can come to supersede old habits and more effortful goal-striving behaviors.

3. FITTLE+ SYSTEMS AND STUDIES

3.1. Guided Mastery

As noted, the path to healthy habits typically involves a phase in which intentions and goals motivate and guide repeated enactments of the desired behavior until the behavior becomes habitual in desired contexts (Wood & Neal, 2007). Research shows that specific, challenging goals consistently lead to higher performance than exhortations to do one's best (Locke & Latham, 2002).[1] One key principle in the design of Fittle+ systems is to have our users continuously engaged in achieving *well-specified behavior-change goals* and to provide interactions and interventions that promote success in achieving those goals. Another key principle is to organize related behavior-change goals into *challenge programs* and to support *guided mastery* whereby users achieve progressively more difficult or complex goals over time (usually weeks to months).

As suggested in Figure 1, Fittle users are asked to set behavioral goals, self-monitor achievement of those goals, and are provided feedback on their goal progress. These behavior-change techniques have been found to be among the top most effective for long-term improvement in diet and physical activity (Samdal et al., 2017). Using tasks that increase in difficulty from simple to hard (graded tasks) is also among the top behavior change techniques for diet and physical activity (Samdal et al., 2017).

Fittle+ challenge programs have been developed by members of our team who are subject matter experts in program design to foster healthy nutrition and physical activity/exercise habits. Challenge programs are aimed at small groups of people ("teams") with similar behavior-change intentions (i.e., goal alignment) and similar entry-level capabilities. Many of the challenge programs are designed to support

[1] The notion of specific goals is consistent with the definition of SMART goals (specific, measurable, achievable, realistic, relevant and timed).

guided mastery by having a static or dynamically computed progression of behavior-change goals that increase in difficulty, or habits that build upon each other. Fittle + applications support the user in mastering each goal before progressing to the next. This approach is motivated by the success of *mastery learning* in education (Bloom, 1968) and cognitive tutoring systems (Anderson, Boyle, Corbett, & Lewis, 1990; Anderson, Boyle, & Reiser, 1985). The approach is also motivated by the success of *guided enactive mastery* (Bandura, 1998) in improving self-efficacy.

For instance, the original Fittle application (Honglu Du et al., 2014) included a NutriWalking program targeting sedentary people who wanted to increase their physical activity and eat better. The program includes nutrition activities: eat slowly, add a serving of vegetables (or a different vegetable if a vegetarian), add a small healthy meal, and keep a food diary. The original NutriWalking program also focused on getting participants to walk more by starting with 15 minutes 3 times a week on flat surfaces and ramping up to 45 minutes 5 times a week on inclined surfaces with some exercises (e.g., jumping jacks) or short jogging sessions added to the walk. Within each activity class, daily goals are assigned, and those goals progress in difficulty. A specialized version of the Fittle app—called NutriWalking—personalized the user's daily goals within the program based on model-based estimates of the user's current aerobic capabilities (Mohan, Venkatakrishnan, Silva, & Pirolli, 2017). The DStress app aimed to improve people's resilience to stress through physical exercise and meditation, and it dynamically modified individual daily exercise goals based on the difficulty of exercise goals completed on earlier days.

3.2. Guided Mastery as an Intervention to Increase Self-efficacy

Guided mastery is also generally considered a therapeutic method of assisting people in raising their self-efficacy (i.e., perception that a task can be accomplished) so they are motivated to attempt, and subsequently accomplish, progressively more difficult tasks that are involved in the implementation of behavioral therapies. For instance, exposure to progressively greater anxiety-provoking situations is the treatment of choice for individuals who evidence problems associated with anxiety disorders (e.g., panic disorder with agoraphobia). In the utilization of guided mastery, a therapist might encourage and assist the individual in accomplishing a situation that is associated with a low degree of anxiety (e.g., walking in the shopping center with a friend) before moving to situations originally associated with a high degree of anxiety (e.g., walking in the shopping center by oneself). As discussed in greater detail below in the context of the DStress app, we have studied and modeled the effects of guided mastery on self-efficacy.

3.3. Teaming

Support for interaction among a team of people engaged in the same behavior-change challenge program was one of the core interventions used in Fittle. Social support is also among the top six behavior-change techniques in terms of effect size (Samdal et al., 2017). Forms of social support can be found in many commercial smartphone-based health behavior change applications, such as MyFitnessPal, WeightWatchers, etc. However, social support in those applications is built around the user's personal social network, such as Facebook or Twitter friends. In Fittle + we have adopted the principle that teams will need to be formed around the challenge programs (community of interest) rather than formed around existing social networks. One reason for this strategy is scalability—convincing members of a social cluster to engage in a program is likely to be less efficient than casting a wide net for people interested in a behavior-change challenge program and then forming teams.

Social support has been shown to have health benefits in its own right (Callaghan & Morrissey, 1993) and increases participation in exercise programs (Richardson et al., 2010). Social- and group/team-based behavior-change techniques have been shown to be effective in supporting behavior change in long-term weight loss (Wing & Jeffery, 2001). Social support may potentially help sustain engagement with health behavior change interventions, and consequently increase efficacy. An observational study of more than 80,000 users in the context of a web-based health promotion intervention revealed that increased social ties within this challenge community directly predicted online engagement and activity completion (Poirer & Cobb, 2012). Similarly, a recent study compared a structured physical activity intervention comprising education, activity monitoring, and online social networking via a Facebook group versus an education-only control showed that online social networking lowered attrition rates in the program (Cavallo et al., 2014). Likewise, in another study, it was found that weight loss in a 6-month, remotely delivered weight loss intervention was strongly associated with engagement within an online Twitter-based social network wherein participants provided each other with informational support (Turner-McGrievy & Tate, 2013).

3.4. Self-affirmation

Self-affirmation interventions typically ask people to think or write about their core values. This technique has been shown to improve health, education, and relationship outcomes with benefits lasting months to years (Cohen & Sherman, 2014). According to many theorists (Cohen & Sherman, 2014), people are motivated to defend their global sense of self-worth. Health communications, such as the psycho-educational materials presented in Fittle+, can be perceived as threatening to the self-worth of people who are unhealthy, which elicits a defensive resistance to processing those communications. It is hypothesized that self-affirming in one domain (e.g., by recalling one's history of kindness to others) boosts global self-worth and reduces the need to be threatened in another domain, such as health behavior change.

3.5. Implementation Intentions

Implementation intentions are mental representations of simple plans to translate goal intentions into behavior under specific conditions (Gollwitzer, 1993, 1999). Interventions designed to foster the setting of implementation intentions typically ask people to specify when, where, how, and (sometimes) with whom to act on a goal intention by using if-then statements of the form: "If I encounter situation *S* then I will initiate action *A*." It is argued (Wieber, Thürmer, & Gollwitzer, 2015) that one reason to focus intervention efforts on implementation intentions rather than goal intentions is that medium-to-large changes in commitment to goal intentions ($d = 0.66$) only lead to small-to-medium changes in behavior ($d = 0.33$) (T. L. Webb & Sheeran, 2006), but implementation intentions have medium-to-large effects on goal attainment ($d = 0.65$) (Gollwitzer & Sheeran, 2006).

Wieber et al. (2015) review the experimental literature and studies of physiological correlates to bolster the hypothesis that two processes are involved in the effectiveness of implementation intentions: (1) the mental representation of situations in which the intended behavior is to take place becomes more accessible and activates the goal intention and (2) a strong associative link between a mental representation of the situation and intended behavioral action effects a heightened readiness to perform the action and the action takes less effort.

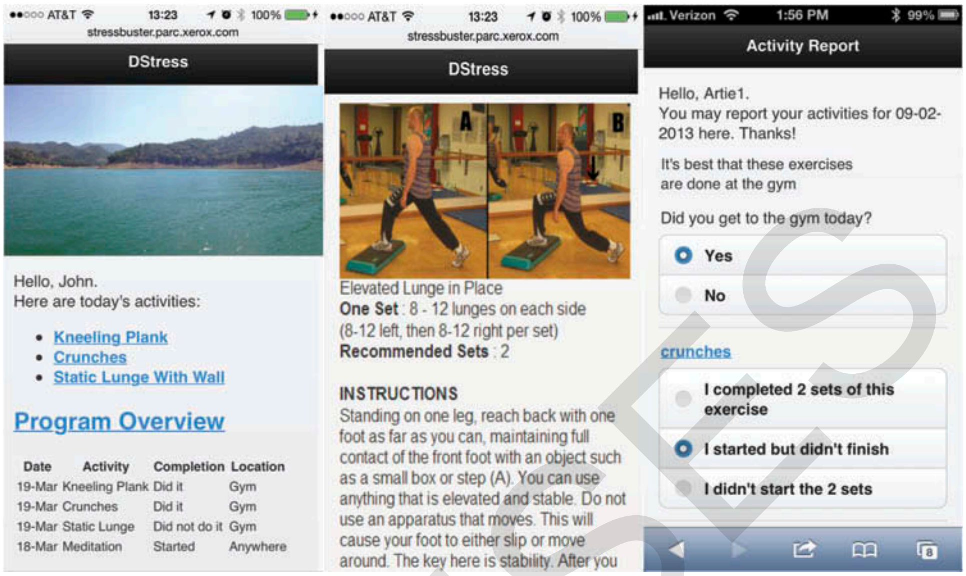
4. RESULTS

4.1. DStress: An Adaptive Algorithm to Build Self-Efficacy through Guided Mastery

One of the major promises of mHealh is the potential for individualization using adaptive algorithms. DStress (Konrad et al., 2015) is a web- and mobile-based system that provides automated coaching on exercise and meditation goals aimed at reducing perceived stress. The coaching algorithms modulate the difficulty of daily exercise and meditation goals based on individuals' performance on the immediately preceding goals. Goal-Setting Theory (Locke & Latham, 2002) predicts that goals need to be challenging enough to be motivating. Self-efficacy (Bandura, 1998) predicts that goals that are perceived as too difficult are unlikely to be attempted. Greater levels of self-efficacy lead to greater likelihoods of achieving a goal. The Attributional Theory of Performance (Kukla, 1972) proposes that the level of *intended effort* motivating a performance will increase with the difference between self-efficacy and the perceived difficulty of achieving a goal. Suggested goals for users should be difficult enough to be motivating, but easy enough to be successfully achieved.

The Konrad et al. (2015) study took place over 28 days. Figure 8 presents screen shots from the DStress system. Participants were sent an email every morning with a reminder to login to DStress. On the DStress homescreen

FIGURE 8. The DStress Application for Reducing Stress: (A) the Home Screen Showing Daily Goals and Part Adherence, (B) Instruction Screen, and (C) Reporting Screen.



(a) (b) (c)

(Figure 8a), users were presented with their current goals, as well as previous activities and their completion status. Pictures and detailed instructions of how to safely and properly perform each activity were available (Figure 8b). Participants were asked to report whether or not they performed their goal for the day and an email reminder was sent in the evening if they failed to report (Figure 8c)

The DStress programs (Konrad et al., 2015) interleaved Exercise Days with Meditation Days and one Rest Day per week. Exercises assigned to individuals came from a pool of exercises that varied in difficulty (always two sets of upper body, lower body, and circuit training exercises). Fourty-six exercises in total were developed by working with three certified trainers, and each one was independently rated by the trainers for difficulty. If a person successfully completed all exercises assigned for a day, an algorithm advanced them to the more difficult level. If they did not succeed at the exercise activities, then they were regressed to an easier level. Additionally, if a person was unable to get to the gym that day to complete the gym-based exercises, the system would propose exercises that could instead be performed at home. Thus, the location accessibility of the exercises adapted based on the users success with getting to the gym. Meditation activities were also adjusted dynamically by increasing or decreasing the number of minutes assigned to meditate (using standard mindfulness meditation instructions).

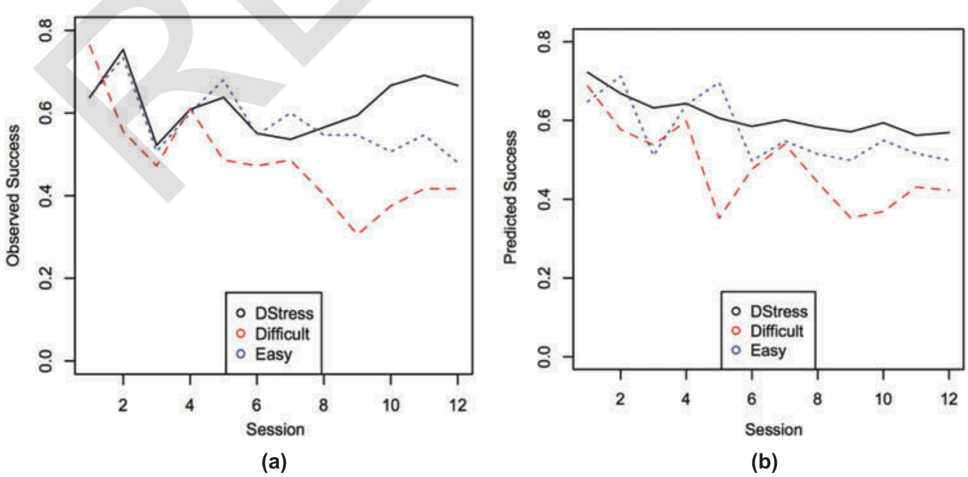
The Konrad et al. (2015) experiment compared three groups of adult participants: (1) a *DStress-adaptive* group (*N* = 19) who used the adaptive coaching system in which goal difficulties adjusted to the user based on past performance, (2) an *Easy-fixed* group (*N* = 24) in which the difficulty of daily goals increased at the same slow rate for all and (3) a *Difficult-fixed* group (*N* = 22) in which the goal difficulties increased at a greater rate. The participants in the DStress-adaptive group self-reported significantly lower stress levels compared to the Easy-fixed and Difficult-fixed groups.

Here, the focus is on the success rates in performing assigned daily goals. By the end of the 28 days study, the DStress-adaptive group was reporting significantly higher level of activity completions than the other two groups (Figure 9a) even though they were performing more difficult exercises than the Easy-fixed group. This increased ability to tackle more difficult goals is consistent with a build-up in self-efficacy.

4.2. Effects of Teaming

Du et al. (2014) performed an eight week field study of *N* = 19 adult participants using an early version of Fittle that provided guided mastery support for diet, physical activity, and stress-reduction. A hierarchical regression analysis indicated that 37% of the variance in success on daily goals was attributable to group membership. Content analysis of the online messaging among team members suggested that high performance groups were more social (commenting on, teasing,

FIGURE 9. Summary Data from Konrad Et Al (KONRAD ET AL., 2015) and the ACT-R Model of Predicted Success Based on Tracing the Experiences on Individual Participants: (A) the Mean Rate of Participants Successfully Completing Assigned Exercises, (B) the Mean ACT-R Predicted Success Rates.



chatting with one another), more supportive (with informational, emotional, or motivational support), and shared more.

Following that study, Du, Venkatakrishnan, Youngblood, Ram, and Pirolli (2016) performed an experiment testing the hypothesis that social support, in the form of small groups or teams, would improve the achievement of daily behavior change goals and reduce the attrition typically observed in digital health programs (Eysenbach, 2005) relative to people working on behavior change in a solitary manner. Figure 1 shows several screenshots of the version of Fittle also used in Du et al. (2016). Users could join teams (Figure 1a) and see profiles of their teammates (Figure 1b). Figure 1e shows the team feed where users can share multimedia posts with the team at any time. Users may also communicate directly with each other through a peer-to-peer messaging system. All teams also include a simple artificial intelligence (AI) agent as a member, named *FittleBot*. FittleBot provides daily tips to the team relevant to their activities, previews the activities for the week, and comments on the daily activities of the team members as a group.

Over the course of an eight-week study with N = 124 participants, Du et al. (2016) found a significant difference in the proportion of daily behavioral goals achieved between people working solo or in teams comprised of 3–9 people in each team (Figure 10). A survival analysis also showed that people working in teams were 66% more likely continue engagement with Fittle when working in teams as opposed to solo (Figure 11).

Real world behavior-change programs, including commercial ones such as Weight Watchers, often employ small groups as part of their technique. These preliminary studies of Fittle system suggest that online teams can have a substantial impact on individual achievement. What remains to be understood are the factors of group composition and group interaction that result in good versus poor groups.

FIGURE 10. Effects of Participating in Small Teams versus Participating Solo in the Nutri-Walking mHealth Program.

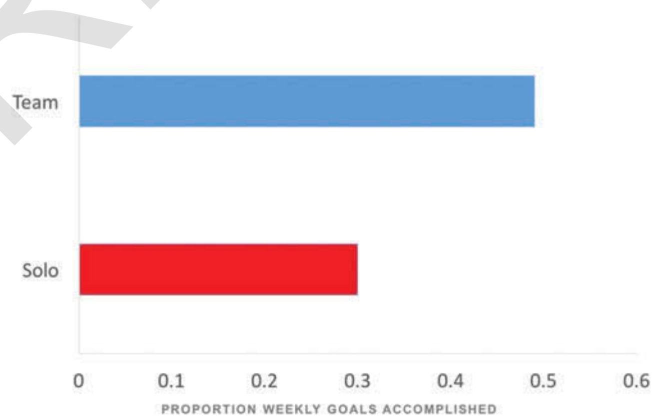
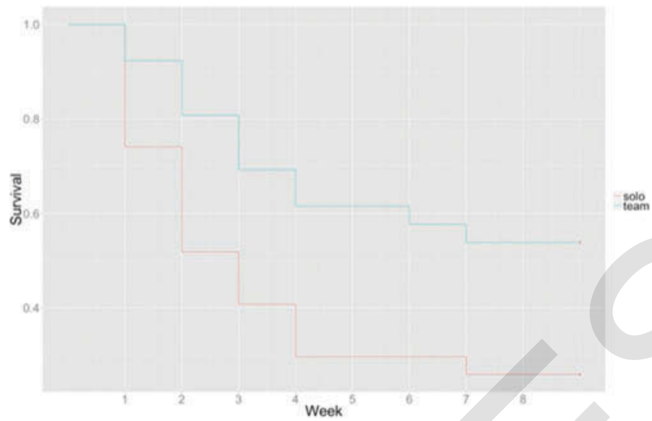


FIGURE 11. Survival Estimates for Continued Engagement with the NutriWalking Program.



4.3. Effects of Self-affirmation

A large body of research (Cohen & Sherman, 2014) has shown that self-affirmation techniques can produce substantial improvements in behavior change in health, education, and relationship outcomes that can last for months to years. Self-affirmation exercises typically involve writing about, or rating, things that a person values (e.g., family, career) (McQueen & Klein, 2006). The exercises appear to boost individual's self-worth and make them more resilient in the face of threats—such as health messaging or fear of failure—and this can produce ongoing positive feedback. Brain imaging studies (Cascio et al., 2016) support the ideas that self-affirmation (a) is rewarding (and pleasurable) as it produces increased activity in the valuation systems (ventral striatum and ventral medial prefrontal cortex) when participants reflect on future-oriented core values (compared with everyday activities) and (b) focuses attention on thinking about the self when reflecting on future-oriented core values, as indicated by increased activity in the medial prefrontal cortex and posterior cingulate cortex. Self-affirmation increases the level of activity in the ventral medial prefrontal cortex (VMPFC), and the level of VMPFC activity during exposure to health messages predicts subsequent behavior change (Falk et al., 2015).

One problem with translating self-affirmation interventions to mobile phone interaction is the length of the exercises in terms of the amount of writing typically requested (e.g., a short essay) or the number of items to be rated. The exercises are appropriate for laboratory, classroom, or face-to-face clinical settings, where paper-and-pen or desktop computer interaction are standard. An advantage of the mobile platform is that it affords more intensive and pervasive interaction. Springer et al. (2018) explored an approach in which initial self-affirmation exercises could be coupled with additional dosing of self-affirmation (*boosters*) throughout the study.

Springer et al. (2018) examined the role of self-affirmation dosage in behavior change and health goal adherence. As far as we are aware, this was the first usage of self-affirmation in a mobile health intervention; this presented challenges in the form of changing contexts in which users completed these self-affirmation exercises and challenges in designing self-affirmation exercises for the slower input affordances on mobile phones.

This mobile health intervention using self-affirmation exercises, PARC Coach, was deployed for $N = 127$ users who were attempting to improve their physical health. The PARC Coach daily goal was to consume the recommended amount (5) of fruit and vegetable servings, as suggested by the National Health Service (NHS, 2015). Before starting the study, all participants reported that they were not currently consuming the recommended amount of fruit and vegetable servings.

Participants were divided into four conditions, in a 2×2 experimental design where the independent variables were the completion of an initial self-affirmation exercise and the weekly completion of mobile self-affirmation boosters. The initial self-affirmation conditions completed a self-affirmation essay manipulation where the users wrote about a cherished value they hold and then were shown threatening health information motivating them to change behavior (McQueen & Klein, 2006). Since the effects of this form of self-affirmation are well established, these conditions allowed us to contrast typical self-affirmation doses with the conditions using self-affirmation boosters. Springer et al. (2018) designed short self-affirmation boosters that consisted of brief self-affirmation exercises and health information that could be quickly and easily completed on a mobile phone. Few previous studies (Cohen et al., 2009; Nelson et al., 2014) have examined the role of multiple self-affirmations in a short time period and none in the context of health behavior change.

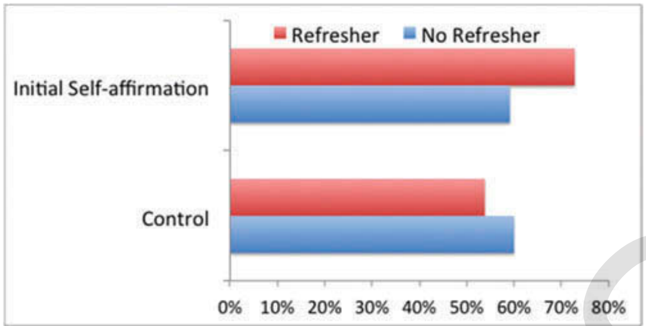
Analysis of 3556 observations from the $N = 127$ participants indicated that higher doses of self-affirmation resulted in statistically greater rates of achieving behavior goals.

Participants who received the maximum dosage of self-affirmation (both initial and booster self affirmation exercises) successfully met over 12% more of their daily fruit and vegetable consumption goals when compared with control (Figure 12). The findings here were twofold: increased self-affirmation dosage results in increased behavior change and self-affirmations can be adapted into a form that is deliverable through mobile devices. This work opened the door to broader usage of self-affirmation in mobile health interventions.

4.4. Effects of Implementation Intentions and Reminders

Research (Wieber et al., 2015) implicates human associative memory mechanisms in the way that implementation intentions produce effects. Based on the ACT-R theory of human memory and cognition, we hypothesized that the strength of implementation intention effects could be manipulated in predictable ways using

FIGURE 12. Percentage of Fruit and Vegetable Consumption Goals Met by Condition.



reminders delivered by a mobile health (mHealth) application. Reminders delivered by mobile devices (e.g., SMS text messages) are common (e.g., Prestwich, Perugini, & Hurling, 2010), but there is no theoretical understanding of their effects.

The ACT-R theory of declarative memory includes a *base-level learning* mechanism that accounts for practice (e.g., reminding) effects and forgetting effects. Declarative memories have a base-level activation value that predicts their probability and speed of retrieval. The dynamics of base-level memory activation are predicted to be related to frequency and timing of reminders, as well as the frequency and timing of actual use of the implementation intentions in performing behavior. The ACT-R base-level learning mechanisms predict that each time an implementation intention is formulated, reminded, or put into practice it receives an increment of activation (a practice effect). However, each increment of activation decays as a power function of time (the forgetting effect). The rate of decay of each increment of activation depends on the strength of activation at the time of the reminding or practice: At longer intervals between remindings or practice, the activation levels are lower and subsequent forgetting occurs less quickly (the spacing effect). When reminding or practice is spaced closely, the forgetting occurs more quickly.

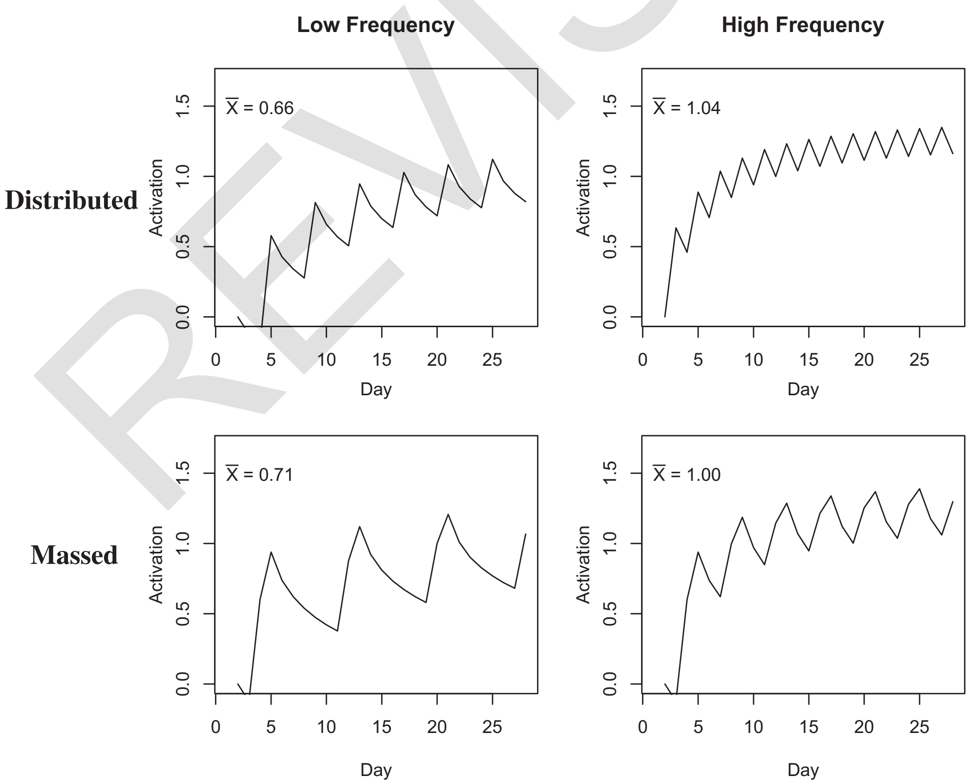
Pirolli et al. (2017) presents an experiment that manipulated the effects implementation intentions on daily behavioral goal success by controlling and manipulating the scheduled delivery of reminders about those implementation intentions. All participants were asked to choose a healthy behavior goal associated with Eat Slowly, Walking, or Eating More Vegetables, and were asked to set implementation intentions. N = 64 adult participants were in the study for 28 days. Participants were stratified by pre-experimental levels of self-efficacy and assigned to one of two reminder conditions: Reminders-presented versus Reminders-absent. Self-Efficacy and Reminder conditions were crossed. Nested within the Reminders-presented condition was a crossing of *Frequency* of reminders sent (High, Low) by *Distribution* of reminders sent (Distributed, Massed). Participants in the

Low Frequency condition got 7 reminders over 28 days; those in the High Frequency condition were sent 14. Participants in the Distributed conditions were sent reminders at uniform intervals. Participants in the Massed Distribution conditions were sent reminders in clusters.

Figure 13 shows the predicted effects of the Pirolli et al. reminding schedules on the base-level activation of implementation intentions. Each peak in Figure 13 corresponds to a day on which a reminder was presented. Reminders are predicted to boost up the base-level activation of participants' implementation intentions but the activation decays without further practice, and distributed presentations of reminders are forgotten less quickly Manipulation of the declarative memory activation of implementation intentions was expected to affect the goal-striving phase of habit formation.

Each plot in Figure 13 also presents the predicted mean activation level of the implementation intention over the full 28 days for each condition (upper left corner of each plot). Note that at Low Frequency of reminders, the mean activation level in the Massed condition is greater than that of the Distributed

FIGURE 13. Simulated Base-Level Learning of Implementation Intentions as a Function of Different Reminder Schedules.



condition, but at High Frequency the mean activation of the Distributed condition is greater than the Massed condition. Thus, there is a predicted interaction of reminder Distribution (Massed, Distributed) by Frequency (Low, High), and specifically the average activation levels for the implementation interventions are predicted to be High Frequency-Distributed >High Frequency-Massed >Low Frequency-Massed >Low Frequency-Distributed. Behavior-change data were used to test for this predicted interaction and the specific ordering of success rates predicted by the model.

There was a significant overall effect of reminders on achieving a daily behavioral goal. As predicted by ACT-R (Figure 13), there was a statistical interaction of reminder *Frequency* by *Distribution* on daily goal success. The total number of times a reminder was acknowledged as received by a participant had a marginal effect on daily goal success and the time since acknowledging receipt of a reminder was highly significant.

5. ACT-R MODELS

5.1. ACT-R Model of Self-Efficacy Using DStress

The ACT-R model for this study (Pirolli, 2016a) assumes that self-efficacy and intended effort are fundamentally the result of declarative memory processes. Past experiences of efficacy at behaviors similar to a target goal are retrieved to produce assessments of self-efficacy and intended effort for the new goal. Consequently, the dynamics of self-efficacy and performance exhibit the dynamics of the underlying memory mechanisms, and exhibit well-known memory phenomena.

In outline, the model involves the following steps:

- A *behavioral goal* is considered for doing *activities* that are believed to have some level of *difficulty* to being performed.
- *Blended memory retrieval to form an assessment of self-efficacy*. Successful experiences are recalled involving activities *similar* to the goal activities. A composite assessment is produced characterizing the difficulty levels of exercises achieved in past experiences, and this is mapped onto an assessment of *self-efficacy*.
- *Blended memory retrieval to form an intended effort level*. Experiences are recalled with similar levels of self-efficacy and perceived goal difficulty. This process produces an assessment of intended effort levels required to achieve success in those past experiences.
- *Predicting success*. Based on the goal difficulty, perceived self-efficacy, and intended effort, the model makes a prediction about the likelihood of success.
- *Choose to do it (or not)*. If the expected probability of success is above a threshold it is attempted.

- *Store new experiences*. If the activity is attempted, the experience is stored in memory and influences future attempts.

Figure 9b shows summary data from the ACT-R model. The model produces a predicted success or failure for each and every exercise on every exercise day for every participant in the Konrad et al. (2015) study. Each point in Figure 9b pools the predicted success data by day and by group (DStress-adaptive, Easy-fixed, Difficult-fixed). In fitting the ACT-R model to the data, we used the default parameter settings suggested for ACT-R simulations. That is, no free parameters were estimated while fitting the model, and the parameters did not differ from individual to individual. For the data displayed in Figure 9, *RMSE* = = 0.083.

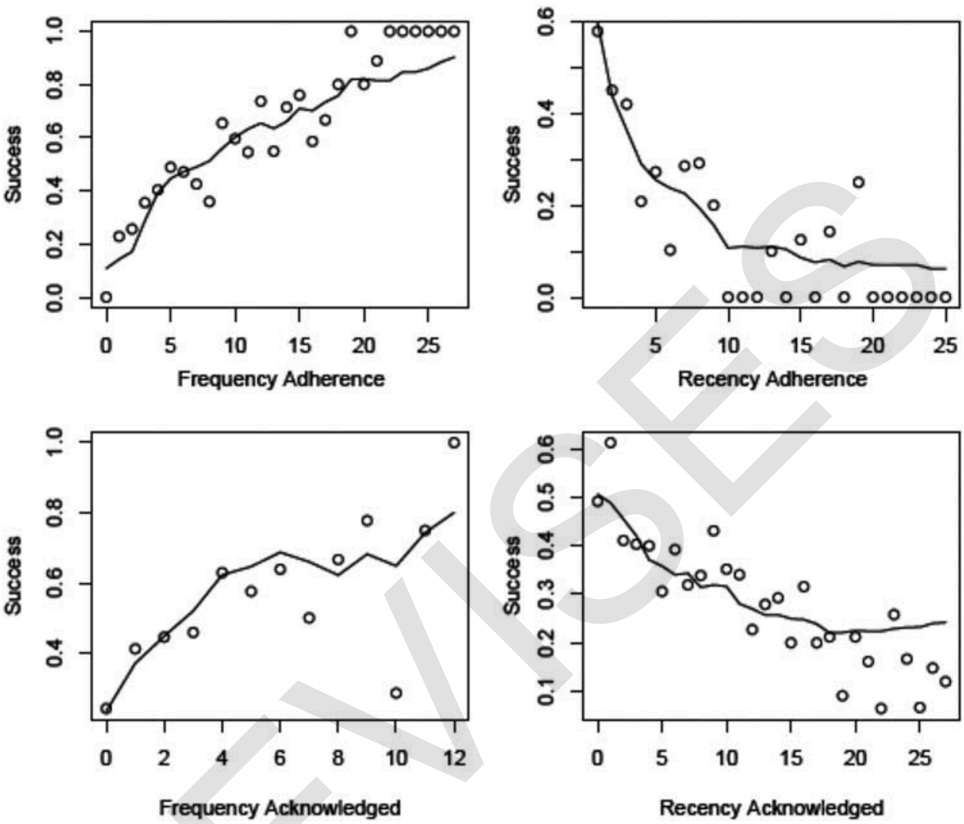
5.2. ACT-R Model of Implementation Intentions

As discussed above, ACT-R theory suggests that behavior change involves dual systems: the goal-striving system dependent on declarative memory plus a habit-forming system that acquires more automatic procedures for performance. Pirolli et al. (2017) fit an ACT-R model dual-system model to the implementation intention experiment. The model includes (a) the goal-striving system dependent on implementation intentions in declarative memory whose strength is affected by reminders and (b) the habit/reinforcement learning system that acquires new behavioral routines through repeated performance.

Figure 14 plots the goal success predictions of this dynamical ACT-R model against the observed data in Pirolli et al. (2017) as functions of past goal adherence and reminders acknowledged. Recency in Figure 14 means the number of days since the last event (performing a goal or acknowledging a reminder) and frequency refers to the cumulative total number of events. The points are the observed probabilities of success at achieving a goal behavior and the lines are the model predicted probabilities. The model fits are to each individual's daily data for the entire course of the experiment. Each point is the mean of the observed individual daily success for participants at a given level of recency or frequency, and similarly the lines are the means of the model's predictions for each individual on each day, pooled by level of frequency and recency. Overall, the cumulative total frequency of reminders is predictive of an increase in goal success, the time since last reminder (recency) is predictive of a decrease in goal success, and the total frequency of past successful goal performance (adherence) is predictive of an increase in success, and time since last successful performance (adherence recency) predict a decrease in goal success.

For these implementation intention data, the ACT-R model is more complex than the one used to model the DStress data. Five ACT-R parameters representing the implicit reward for achieving a behavior goal, the utility value of a new habit, the utility learning rate, and scaling and slope parameters for base-level learning in declarative memory were estimated simultaneously along with six scaling and weight parameters that mapped ACT-R memory activation and production utility values onto the

FIGURE 14. Fit of the ACT-R Dual-System Model to Daily Success in Performing Behavior Goals.



empirical goal-success rates. These parameters were not varied for each individual simulated. The Brier score on the fit of the model to the data was 0.1724. Full details on the model an parameter estimation can be found in Pirolli et al. (2017). Overall the dual-system ACT-R model theory provides a good fit to the individual-level data.

Overall, across the DStress and implementation intention models, ACT-R provides an integrated computational account that refines self-efficacy, Goal Setting Theory, the Attributional Theory of Performance, and habit formation predictions.

6. GENERAL DISCUSSION

There are two main contributions of this article. First, we propose the concept of scaffolding interventions as digitally delivered interactions that instantiate behavior change techniques that support people in developing healthy habits. Second, we present predictive models developed within a unified computational cognitive architecture that combines multiple psychological mechanisms involved in two independent studies of different scaffolding interventions. We also propose that this work serves as a launching point for richer exploration of how to develop more sophisticated, dynamic, and intelligent coaching support for healthy lifestyle change.

6.1. Scaffolding Interventions

The Fittle+ systems and studies have been aimed at exploring and understanding mHealth behavior change systems as a process of building a set of healthy habits. The approach involves a combination of behavior-change techniques (Michie et al., 2014) found to be effective (Cohen & Sherman, 2014; Gollwitzer & Sheeran, 2006; Samdal et al., 2017) implemented as specific scaffolding interventions on an mHealth platform. The scaffolding interventions are aimed at increasing people's adherence to specific behavior-change goals, with the ultimate goal of helping them develop healthy habits. Many mHealth systems (Consolvo, Everitt, Smith, & Landay, 2006; Consolvo et al., 2008; Consolvo, McDonald, & Landay, 2009; Klasnja, Consolvo, & Pratt, 2011) focus on one or just a few variants of behavior (e.g., increased physical activity) and on one or a few intervention techniques. Our approach can be viewed as drawing upon traditions in education, classical behaviorism, and cognitive skill acquisition that view desirable complex behaviors as systems that can be decomposed into elements that can be built up and organized through various interventions and scaffolding that may be subsequently faded (although not necessarily).

Each of the particular scaffolding interventions presented in this article could benefit from further research. Particularly intriguing is the teaming intervention. As noted above, Du et al. (2014) found that 37% of the variance in individuals' goal achievement success was due to variation in the teams they were in. But we do not understand what social or communicative interactions are causal, nor the underlying mechanisms involved. A deeper understanding of these mechanisms could lead to interesting interventions focused on team formation and team dynamics that produce large improvements in healthy behavior. Such research would also be an opportunity for pushing computational theories of individual cognition, such as ACT-R, further into the realm of social interaction and social psychology.

Digital health platforms have the potential to support new empirical methods that could revolutionize the study and optimization of scaffolding interventions, accelerating the attempts to harmonize the vast literature on behavior-change techniques and yield scalable digital health platforms (Michie et al., 2013; Samdal et al., 2017). One such method is the Multiphase Optimization Strategy (MOST; Collins, Murphy, & Strecher, 2007) that could be used to efficiently select and refine scaffolding interventions based on their effectiveness. Another is the Sequential Multiple Assignment Randomized Trial method (SMART; Collins et al., 2007) which is suited for understanding sequentially delivered interventions, and for tailoring time-varying adaptive interventions. Micro-randomized trials (Klasnja et al., 2015) combine aspects of within-participant and between-participant experimental designs in ways that greatly increase statistical power. Each of these methods extends traditional experimental designs and statistical techniques in ways that are more congruent with how digital platforms actually operate and collect rich data. They offer new ways of studying multiple scaffolding interventions or variants in more efficient ways than standard randomized controlled trial designs. Machine learning techniques, such as reinforcement learning (Yom-Tov, Kozdoba, Mannor, Tennenholtz, & Hochberg, 2017), can also be applied to better understand and optimize the effects of specific contextually tailored interventions.

"Scaffolding" in the learning sciences may typically imply the intention that the scaffolding supports for learning will eventually be withdrawn (Reiser, 2004; Reiser & Tabak, 2014). However, many interventions that may have been originally intended as educational scaffolding have become part of our everyday environment, such as calculators and structured code editors. It is conceivable (for instance, see Stawarz, Cox, & Blandford, 2015) that new behaviors may be supported with scaffolding (e.g., reminders), but then be triggered only if that scaffolding provides the necessary cues in the environment (e.g., will not occur unless a reminder is sent). In other words, the new habit is contingent on the scaffolding cues, and the intervention cannot be removed without affecting the habit's performance. This is not necessarily a problem, as much of our modern life depends on continuous support from digital infrastructure, but it is important to realize that maintaining a habit as scaffolding interventions are removed may require attention over and above the initial building up of the habit in the presence of scaffolding interventions.

Much remains to be understood about how and when to combine scaffolding interventions. It is possible that scaffolding interventions may combine to produce benefits beyond the sum of their independent effects. There may be person-dependent interactions. There may even be negative interactions among scaffolding interventions. Just as there are sometimes drug-drug interactions that must be avoided in medical treatment, there may be particular combinations of interventions that cancel out each other's effects, or perhaps have negative consequences. One can also imagine that piling up scaffolding interventions in an engagement with users might have an overall diminishing returns (or negative returns)—e.g., reminders associated with different interventions might increase in number to the point that people become annoyed and inattentive, or completely disengaged.

6.2. Predictive Theory and Modeling

As part of this effort, we have begun to develop a predictive modeling approach that builds upon well-established computational cognitive theory. In essence, we have taken the ACT-R theory of cognitive skill acquisition (Anderson, 1982; Anderson, 1987; Anderson, Conrad, & Corbett, 1989) and extended it to habit formation in the ecology of everyday life. As argued elsewhere, such fine-grained predictive models will need to be developed to better predict and control fine-grained, dynamic digital, and mHealth interventions (Riley et al., 2011). Progress in predictive modeling (Martín et al., 2014; Pirolli, 2016a) should lead to the development of user modeling approaches that support the personalization of interventions (Spruijt-Metz et al., 2015). This also opens up a path for scientific psychology to extend laboratory-developed theories and models out into the ecology of everyday life, where meaningful behavior happens (Baumeister et al., 2007).

To repeat an argument made elsewhere (Pirolli, 2016a, 2016b; Pirolli et al., 2017), the motivation for developing predictive theories of scaffolding interventions by extending theories of the human cognitive architecture rests on four theses (Anderson, 2002; Newell, 1990): (a) the *Integration Thesis* that cognitive architectures provide a unified account of how the mind functions and can provide a basis for an integration across specialized theories and techniques of behavior change, (b) the *Decomposition Thesis* that longer-term behavior change can be decomposed to learning and intervention events occurring at a much finer granularity of time, (c) the *Modeling Thesis* that models in cognitive architectures can provide a basis for bridging those events at the small scale to the dynamics of behavior change occurring at the large scale, and (d) the *Relevance Thesis*, that longer term changes and outcomes can be improved by modeling and predicting specific scaffolding interventions in contexts that are occurring at the smaller time scales in the everyday lives of people wishing to change.

HCI has had a long history of appropriating psychological science to improve personal computing (Card, Moran, & Newell, 1983) and, in return, being a crucible for the advancement of psychology. With mHealth, and digital health more generally, there is an opportunity to develop a new science and engineering of personalized computing that supports long-term improvements in lifestyle and health.

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