A SOCIAL COGNITIVE SMARTPHONE APPLICATION FOR IMPROVING PHYSICAL ACTIVITY IN ADULTS

BY

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DISSERTATION

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Abstract

The pervasiveness, broad reach, and processing capabilities of consumer technologies, including the internet and smartphone devices, has driven the rapid development of research and commercial applications meant to promote physical activity. Unfortunately, researchers have found that commercial physical activity applications (apps) are not often effective, and are not typically evidence-based. The purpose of this study, which was guided by the multiphase optimization strategy (MOST), was to test the individual and combined efficacy of two theory-driven smartphone app modules designed to promote physical activity: guided hierarchical goal setting and points-based feedback. Participants (N = 116) were recruited to participate in a 12-week home-based exercise program, and randomly assigned to one of four conditions. All individuals received a base-app, which contained three components common to eHealth interventions: physical activity tracking, individualized feedback, and weekly theory-based educational modules. One group received this app alone; a second received the base-app plus a points-based feedback module which awarded points, levels, and badges for engaging in physical activity and other in-app functions; a third received the base-app plus a guided goal setting component which aided individuals in setting both distal and proximal physical activity goals by providing goal recommendations and windows that urged gradual progression; and a fourth condition that received all app components. Results demonstrated that individuals in all conditions increased accelerometer-measured moderate to vigorous physical activity (MVPA) by more than 11 minutes per day across the intervention period, while those with access to the points-based feedback module demonstrated higher levels of MVPA when compared to those without the module. Additionally, these individuals demonstrated more favorable outcomes on a number of psychosocial measures (i.e., barriers self-efficacy, exercise self-efficacy, perceived goal setting ability, outcome expectations) and app usage across the intervention. Those with access to in-app goal setting also had higher levels of app usage relative to those without the component. Overall, these findings provide important information for those interested in developing apps aimed at improving physical activity, and lay the groundwork for additional research.

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Chapter 1: Introduction

A physically active lifestyle is necessary for the maintenance of health and quality of life across the lifespan. Indeed, national and international agencies such as the Centers for Disease Control and Prevention (CDC) and the World Health Organization (WHO) have recommended minimum levels necessary to achieve positive health benefits and reduce the likelihood for becoming chronically ill. The WHO recommend that adults engage in moderate intensity aerobic activity for at least 150 minutes per week, or vigorous intensity aerobic activity for at least 75 minutes per week, and this can be accumulated in bouts of at least 10 minutes. Additionally, it is recommended that individuals engage in muscle-strengthening exercise involving major muscle groups on at least two days per week (WHO, 2011a). Failure to engage in sufficient levels of physical activity has been associated with a host of chronic diseases, including increased risk for cardiovascular disease, obesity, type-II diabetes mellitus, several types of cancer, and bone disease (Warburton & Bredin, 2016; Warburton, Nicol, & Bredin, 2006; WHO, 2011a).

In addition to protecting against the onset of morbidity, researchers have consistently demonstrated that engaging in both acute and chronic physical activity can yield substantive health benefits across the lifespan in both healthy individuals and those with chronic morbidities. For example, a growing body of evidence supports the relationship between both acute and chronic physical activity and enhanced cognition. In children, acute and chronic aerobic activity have been associated with improvements in elements of attention, as well as with academic achievement (Hillman et al., 2009, 2014; Hillman, Kamijo, & Scudder, 2011). Importantly, studies examining the relations between physical activity and academic performance in school children have reported either neutral or positive effects, which may have implications for the role of physical education and recess in the school day (Hillman, Erickson, & Kramer, 2008).

The relationship between physical activity and cognition has been most extensively studied is the older adult population. Research suggests that some aspects of cognition peak during the third decade of life and decrease continuously through older adulthood (Diamond, 2013; Harada, Natelson Love, & Triebel, 2013; Salthouse, 2009). These decrements are most pronounced in areas associated with higher order executive processing (i.e., working memory, inhibition, cognitive flexibility, planning and coordination; Colcombe et al., 2006), and these declines contribute to cognitive impairment, dementia and reductions in one's overall quality of life and ability to live independently (Colcombe et al., 2006; Erickson et al., 2011). Researchers have demonstrated that the application of aerobic physical activity intervention, even in late life, can promote maintenance and growth in these brain regions (Colcombe et al., 2006; Erickson et al., 2009, 2011, 2012), in turn improving executive functions (Erickson et al., 2011). Finally, researchers have found similar improvements in cognition among a variety of special populations, including cancer survivors. These findings are of particular importance, as improvements in treatment techniques over the last several decades has led to greater numbers of cancer survivors, and as many as three in four survivors experience treatment-related decrements to cognitive function (Hartman, Marinac, Natarajan, & Patterson, 2014).

Another important domain of health that is maintained across the lifespan via regular physical activity is quality of life. Among older adults, health-related quality of life is of utmost importance, and many individuals prioritize it above longevity as they age (Rejeski & Mihalko, 2001). Evidence supports the position that physical activity enhances quality of life in healthy adults (Bize, Johnson, & Plotnikoff, 2007), older adults, and a number of special populations, including cancer survivors (Rogers et al., 2015), individuals with multiple sclerosis (Motl & McAuley, 2014), and those with chronic liver disease (Hickman, 2004). In total, research seems to indicate that beyond adding years to one's life, engaging in regular physical activity enhances the quality of those years (Acree et al., 2006; Rejeski & Mihalko, 2001).

Despite the clear benefits of a physically active lifestyle, one in three adults engage in no leisure-time physical activity, and half fail to meet public health recommendations (American Heart Association, 2013). Though staggering, these numbers are of little surprise: physical exercise is a complex and dynamic behavior, requiring different motivators as individuals attempt to adopt and then maintain the behavior in the long term (Colcombe et al., 2006; Fjeldsoe, Neuhaus, Winkler, & Eakin, 2011; King, 2001a; McAuley, 1993). Researchers have developed and implemented a variety of behavioral theories in order to better design health behavior interventions and interpret their outcomes. Albert Bandura's social cognitive theory (1986, 1997) has received considerable support across a variety of health behaviors, including sexual health (e.g., Bandura, 1994), dietary behavior (e.g., Hebert et al., 2001), sitting behavior (Fanning et al., 2016), and physical activity (e.g., Fanning et al., 2015; Gothe, Fanning, et al., 2014; Rogers et al., 2015; White, Wójcicki, & McAuley, 2012). Within social cognitive theory, Bandura specifies a core set of determinants of behavior, including *knowledge* of the risks and benefits associated with health practices, one's beliefs in their personal ability to carry out a specific course of action (i.e., one's perceived *self-efficacy*), the *outcome expectations* one holds regarding the expected costs and benefits of a given behavior, the *goals* and related strategies put in place by an individual, and the perceived social and structural *facilitators and impediments* to successfully engaging in a behavior (Bandura, 1997, 2004).

One's beliefs in their personal efficacy to produce a behavior plays a central role in successful behavior change. Individuals are unlikely to be sufficiently motivated to continue a difficult behavior, especially in the face of setbacks and challenges, if they have little belief in their ability to be successful (Bandura, 1997, 2004). These beliefs are built from four main sources of information: previous mastery experiences, vicarious experiences, social persuasion, and one's perceptions of their physiological and affective responses to the behavior. Mastery experiences are theorized to exert the greatest influence on efficacy beliefs (Bandura, 1997).

Though efficacy beliefs influence behavior directly, Bandura (2004) also posits that they have an indirect influence on behavior by acting upon the other three determinants (i.e., outcome expectations, goals, and sociostructural facilitators and impediments). Additionally, both outcome expectations and perceived sociostructural factors influence the types of goals that one sets, and both goals and outcome expectations have a direct influence on behavior. Finally, relationships between key social cognitive constructs are bidirectional (Bandura, 1997, 2004).

Notably, self-regulation and effective goal setting are important predictors of initiation and maintenance of health behaviors (Anderson, Wojcik, Winett, & Williams, 2006; Bandura, 1997, 2004; McAuley, Mullen, et al., 2011). Effective goals include both proximal (i.e., short-term) and distal (i.e., long-term) goals. Distal goals, such as the desire to meet recommended levels of physical activity or the desire to lose a certain amount of weight, serve to provide direction for behavior. It is important, however, that these distal goals are broken into challenging but attainable short term goals that build toward the larger goal. As an example, a low-active individual who aims to achieve the distal goal of 150 minutes of walking per week may begin by setting a goal to walk at a moderate pace on three days per week for 15 minutes per day over the next two weeks. After two weeks, the individual should be encouraged to evaluate and revise the goal such that it continues to build toward the desired distal goal. A strong sense of self-efficacy will guide an individual to set and achieve more ambitious goals, and highly specific proximal goals provide continuous and rising indicants of mastery, which in turn enhance efficacy beliefs (Bandura, 1997, 2004).

The social-cognitive framework has been useful for the development and evaluation of effective physical activity interventions. For instance, McAuley and colleagues (2012, 2013) delivered a 6-month exercise intervention via DVD to community dwelling older adults that was built upon social cognitive principles. The program included six DVD-delivered exercise sessions that progressed in complexity and difficulty in order to promote a sense of efficacy via mastery experience. Older adult models were featured in the DVD in order to enhance self-efficacy via vicarious experience, and regular, tailored feedback further underscored positive mastery experiences. This innovative design enhanced physical activity and function, and was able to do so in the home, thereby enhancing the program's disseminability (Gothe, Wójcicki, et al., 2014; McAuley et al., 2012, 2013; Wójcicki et al., 2014).

The DVD-based methods employed by McAuley and colleagues allowed the researchers to deliver a well-designed physical activity program to a broad population, providing a foundation for future home-based physical activity programs. The work also highlights several areas for additional research that have yet to be explored. For example, feedback provided in home-based physical activity programs is often compiled manually by research staff, delaying receipt of the feedback and reducing the program's scalability. This may impact the effectiveness of the feedback, which should be both specific and timely (Neville, O'Hara, & Milat, 2009; Norman et al., 2007; Rovniak, Hovell, Wojcik, Winett, & Martinez-Donate, 2005). Moreover, when the program terminates and intervention participants are suddenly left to continue a health behavior on their own, they often find it difficult to do so. Researchers have long sought methods for promoting maintenance of physical activity following the end of an intervention (Fjeldsoe et al., 2011; Marcus et al., 2000; McAuley et al., 2007).

In order to provide ongoing, dynamic, and tailored content that can be distributed broadly, some have embraced emerging popular technologies, and particularly the smartphone, as platforms for intervention delivery. Smartphone devices are nearly ubiquitous, and many owners carry their device at all times (Smith, 2015). Furthermore, these devices carry a variety of useful sensors (e.g., accelerometers, GPS), and they are data-driven, providing the ability to delivery individually-customized, highly specific feedback (Dufau et al., 2011; Fanning, Mullen, & McAuley, 2012; Miller, 2012). These features suggest that the platform may be unique in its ability to consistently monitor behavior and provide immersive, theoretically-driven intervention material. Still, the majority of published studies using mobile phones in the physical activity context have primarily relied on short-messaging service (SMS) to deliver feedback and short tips, and to collect self-report data (Fanning et al., 2012). Further research is warranted that utilizes the unique features of the smartphone to target important theoretical constructs and to promote long term behavior change.

The paucity of work employing complex designs via the smartphone is driven in large part by the time taken to conceptualize, fund, conduct, and publish research; a cycle that has been placed by some estimates at seven years (Glasgow, Phillips, & Sanchez, 2014; Riley, Glasgow, Etheredge, & Abernethy, 2013). The process of technological development typically outstrips this research cycle, limiting the utility of published findings. In an effort to increase the efficiency of this process, a variety of alternative methods for building and evaluating mobile health (mHealth) interventions have been developed. A framework that has received a great deal of attention in recent years is the multiphase optimization strategy (MOST; Collins, Murphy, Nair, & Strecher, 2005; Collins, Murphy, & Strecher, 2007). MOST utilizes a three-phase process: during the *preparation* phase, researchers use any of a number of study designs to simultaneously test a variety of intervention components, allowing for the identification of effective components for future iterations of the research design. These decisions can be made based on a number of criteria including statistical significance, effect size, or cost of implementation. Factorial research designs are often used during this phase, as they allow researchers to test the influence of individual and combined research components, and researchers can do so with smaller sample sizes (Collins et al., 2007).

Following the *preparation* phase, components that were deemed effective are retained in the *optimization* phase, which is often thought of as a "first draft" intervention. During this phase, the goal is to identify the most effective dose required for the active intervention components, and once again this is often tested using a factorial design. Finally, during the *evaluation* phase, the active components are delivered at the optimal dose in a standard randomized controlled trial (RCT). The use of iterative testing frameworks allows researchers to more quickly publish useful findings while arriving at an optimized intervention design (Collins, Dziak, Kugler, & Trail, 2014; Collins et al., 2007; Glasgow et al., 2014).

The purpose of the present project, the Multiphase Activity Promotion Study (MAPS), was to develop and test the efficacy of a theoretically-driven smartphone application for enhancing levels of physical activity. The specific aims are as follows:

1. To determine which intervention components are the most effective for increasing physical activity behavior. These may work alone or in combination. To test this aim, we collected objective physical activity data at the beginning of the study and during the final week of the program. We then conducted a repeated-measures factorial analysis of variance

(RM-ANOVA) to determine which component(s) contributed to the greatest increase in physical activity. It was hypothesized that the interaction between time and each intervention component would be significant, as would the interaction between time, goal-setting, and points.

2. To determine which intervention components contributed to the greatest increase in key social cognitive constructs, including various domains of self-efficacy, outcome expectations, and overcoming barriers (i.e., sociostructural factors). We collected questionnaire measures of these constructs at baseline and program completion, and again conducted factorial RM-ANOVAs. It was hypothesized the analyses would reveal significant two-way and three-way interactions between time and each intervention component for each of the social cognitive constructs.

3. To examine the use and usability of the theoretically-designed activity intervention delivered via smartphone application. We collected usage and compliance rates for each aspect of the mobile intervention, technical challenges were recorded, and qualitative evaluations were completed following the intervention. It was hypothesized that each intervention component would contribute to higher usage rates, and the greatest usage rates would be seen among individuals with access to both components. Moreover, while a small amount of decay in use was expected, it was hypothesized this effect would be small due to the presence of ongoing individualized feedback.

MAPS is significant as it is the first study to harness the dynamic and interactive nature of the smartphone to target key social cognitive constructs with the goal of improving physical activity behavior. It is further guided by the first phase (i.e., the *preparation* phase) of the MOST framework, employing a factorial design to simultaneously test the efficacy of two intervention components: a guided, interactive goal setting module and a points-based feedback system. The findings of this study will be of immediate use to physical activity researchers and commercial developers alike, and will serve as the basis for future *optimization* and *evaluation* phase research studies.

Chapter 2: Literature Review

This study utilizes a social cognitive framework to guide the development of an automated and tailored smartphone application meant to improve physical activity behavior in healthy adults. It is further guided by the first phase (i.e., the *preparation* phase) of the MOST framework, employing a factorial design to simultaneously test the efficacy of two intervention components: a guided, interactive goal setting module and a points-based feedback system. If successful, MAPS will help to advance the field of health promotion by identifying a set of intervention techniques that can be applied across a variety of technological platforms. To underscore the need for such a design, this section contains a brief review of the following: current physical activity recommendations for healthy adults and older adults; the risks of inactivity and benefits of physical activity for adults and older adults; the use of social cognitive theory in the design and evaluation of physical activity interventions; the use of internet and mobile technologies for the study of physical activity behavior; and the development of novel frameworks for the rapid evaluation of mHealth interventions.

Current Physical Activity Recommendations for Adults and Older Adults

In 2008, the population of the United States received their first federal guidelines for physical activity by way of the Physical Activity Guide for Americans (U.S. Department of Health and Human Services, 2008). Within this document, the U.S. Department of Health and Human Services (HHS) compiled clear physical activity recommendations for children, adults, and older adults with the goal of clarifying and updating recommendations issued by the CDC and the American College of Sports Medicine in 1995 (Pate et al., 1995). First, the authors of the 2008 guidelines delineated between “baseline physical activity” (i.e., light-intensity activities typically encountered in daily life) and “health-enhancing physical activity” (i.e., physical activities beyond those encountered in typical life). They further detailed four distinct activity categories, each with a brief summary of associated health effects (see Table 1).

The guidelines recommend that healthy adults strive to fall within the *medium* or *high* categories, as these individuals can expect a reduced risk of premature death, stroke, cardiovascular disease, type II diabetes, and depression. With increasing minutes of activity, additional health benefits are obtained such that those engaging in approximately 300 minutes of aerobic activity per week will have a reduced risk of breast and colorectal cancer, and will be more likely to maintain a healthy weight. The HHS note that for every two minutes spent in moderate aerobic activity, individuals can substitute one minute of vigorous activity. Accordingly, an individual can exercise at a vigorous intensity for 75-150 minutes per week, or an appropriate combination of moderate and vigorous aerobic activity, to fall within the *medium* category. Finally, in addition to weekly aerobic activity, the HHS recommends that healthy adults engage in moderate to vigorous intensity muscle-strengthening exercises involving all major muscle groups on at least two days per week.

Recommendations specific to healthy older adults are identical to those for healthy adults in general, with several important distinctions. Although it is recommended that older adults engage in at least 150 minutes of moderate intensity aerobic physical activity per week (or an equivalent combination of moderate and vigorous aerobic activity), the HHS recognizes that many members of this population live with chronic conditions that may preclude these individuals from being sufficiently active. In these instances, it is recommended that older adults engage in as much activity as their physical state will allow. The importance of balance-oriented activities is also stressed as a means of reducing fall risk. Balance training (e.g., backwards walking, standing from a seated position, toe walking) should be performed on at least three days per week, in addition to other aerobic and muscle-strengthening activities (HHS, 2008).

Finally, information is provided to aid inactive adults and older adults in achieving recommended levels of physical activity. The most important of these tips is an emphasis on gradual progression such that early aerobic and strengthening activities should be of light or moderate intensity and performed in short bouts throughout the week. As a part of this advice, individuals are told to expect to progress slowly over a matter of months (HHS, 2008). In total, these guidelines help to set the stage for individuals who are interested in protecting their health via physical activity.

The Risks of Inactivity and the Benefits of Physical Activity

The Physical Benefits

Since the mid twentieth century, an astonishing body of work has demonstrated with consistency that physical activity has beneficial effects on myriad domains of health. Concurrently, rates of inactivity have increased dramatically such that nearly one in three individuals is insufficiently active (i.e., failing to meet physical activity recommendations), and 17% of the global population is fully inactive (Kohl et al., 2012). Among adults in the U.S., inactivity becomes more prevalent with increasing age, and women and minority populations are less likely to meet recommendations (CDC, 2014b). Rates of inactivity are driven largely by advances in workplace and leisure technologies (e.g., computer and internet technologies, television and streaming video, the ubiquitous use of automobiles for transportation) that promote efficiency but disincentivize physical activity (Haskell et al., 2007; Kohl et al., 2012). Increasing rates of inactivity on a global level, coupled with its associated health and economic risks, have caused many to consider inactivity to be one of the greatest public health threats of the 21st century (Blair, 2009; Haskell et al., 2007; Kohl et al., 2012).

The health benefits of engaging in regular physical activity are tremendous. In studying the risk of all-cause mortality, researchers employing longitudinal designs with long-term follow-up periods have concluded time and time again that physical activity exerts a protective effect against mortality. In the renowned Harvard Alumni Study, researchers examining individuals over the course of up to 16 years (N=16,936) found that risk for death decreased steadily with increasing physical activity-related energy expenditure. Among those expending at least 2000 kcal per week, risk of death was 25-33% lower when compared to less active men (Paffenbarger, Hyde, Wing, & Hsieh, 1986). More recent evidence suggests that a weekly energy expenditure of as little as 1000 kcal is sufficient to produce a 20-30% reduction in all-cause mortality (Lee & Skerrett, 2001).

Copious evidence supports this relationship for more specific diseases as well. More than a half-century of work has demonstrated that physical activity is an important predictor of cardiovascular disease (CVD) risk (Kohl, 2001). In the US, CVD affects approximately one in three adults, and is the leading cause of death: 610,000 individuals die of CVD per year, accounting for one in four deaths (CDC, 2015). In a seminal study of London civil servants, Morris and colleagues (1953) found that the incidence of coronary heart disease (one component of CVD) was lower among the active conductors and ticket-takers of London buses when compared with drivers who remained seated on the job. This relationship held when they later compared postmen to government telephone operators and other sedentary government workers (Morris et al., 1953; Paffenbarger, 2001). In the intervening years, a great number of studies have been published that underscore the role of physical activity in the prevention of CVD. For example, Kohl (2001) conducted a systematic review of the influence of physical activity on CVD. Findings indicated that level of physical activity was causally and inversely related to CVD incidence in a dose-response fashion, and this relationship was the most robust for ischemic heart disease. Li and Siegrist (2012) conducted a meta-analysis wherein they examined only prospective cohort studies with long-term follow-up periods (i.e., ≥ 5 years) and large sample sizes (i.e., $n \geq 1000$), yielding data on greater than 650,000 individuals who were initially free of CVD. For both men and women, engaging in a high levels of leisure-time physical activity resulted in a reduction in risk of CVD by 20-30%, and moderate amounts of leisure-time physical activity resulted in a 10-20% reduction in risk, indicating a dose-response relationship. Moderate levels of occupational physical activity also contributed to a reduction in risk of CVD by 10-20%.

The role of physical activity in the prevention and management of type II diabetes mellitus has also received considerable attention. Nearly 30 million adults in the U.S. live with type II diabetes, with higher prevalence among minority populations. The CDC estimate that one in four individuals with diabetes is undiagnosed. Diabetes is costly: $245 billion are lost per year to medical costs and lost productivity for those who have been diagnosed. Additionally, living with the disease increases an individual's risk for a variety of co-morbidities, including blindness, kidney failure, heart disease, stroke, and loss of limbs. Ultimately, risk for pre-mature death is increased by 50% in this population (CDC, 2014a; Knowler et al., 2002; Tuomilehto et al., 2001). Several rigorous studies have demonstrated that physical activity is an effective means of preventing the onset of type II diabetes. One such example is the Diabetes Prevention Program (Tuomilehto et al., 2001). Researchers randomized 523 overweight adults with impaired glucose tolerance (an important predictor of subsequent diabetes), into an information-only control condition or an intervention condition. These individuals were provided with tailored physical activity and diet recommendations and worked with the staff to set weight loss and physical activity goals. Over the course of the first year of the study, intervention participants increased physical activity levels, made positive dietary changes, lost weight, and had a more favorable metabolic profile when compared with both baseline levels and the control condition. Importantly, over the course of six years, the prevalence of diabetes was 58% lower in the intervention group when compared with those in the control condition (Tuomilehto et al., 2001). In addition to this protective effect, physical activity has an independent and beneficial effect on several important metabolic functions associated with the management of the disease for those who have been diagnosed, including glycemic control and insulin action (Hayes & Kriska, 2008).

Physical activity also holds promise for the prevention of cancer occurrence and recurrence, with the strongest evidence for breast and colorectal cancer (Friedenreich, Neilson, & Lynch, 2010; Thune & Furberg, 2001; Warburton et al., 2006). Thune and Furberg (2001) conducted a systematic review of the influence of physical activity on both general and site-specific cancer. The authors identified 17 observational studies investigating the relationship between physical activity and overall cancer risk and found that 10 studies contained positive results, but the relationship was weaker in women than in men. Other meta-analytic evidence (Shephard & Futcher, 1997) has reported a 30% decrease in risk for physically active men, but they did not find a significant effect for women. Thune and Furberg (2001) found the most compelling evidence for colorectal cancer (48 studies containing 40,674 colorectal cancer cases), and breast cancer (41 studies containing 108,031 breast cancer cases). For both sites, moderate to vigorous physical activity had a protective effect against occurrence of cancer in a dose-response manner. In a systematic review of epidemiological studies examining the relationship between moderate to vigorous intensity physical activity and cancer, Friedenreich et al. (2010) found that those engaging in the highest levels of physical activity had a reduced risk for colon cancer of 20-

25%, and a reduced risk for breast cancer of approximately 25%. The authors also noted that the evidence suggests there is a dose-response relationship between physical activity participation and cancer risk for both sites. Finally, they reported that exercise of about one hour per day appears to confer a benefit for endometrial cancer risk, although this evidence was less robust than that supporting breast and colorectal cancer.

Compelling evidence also suggests that physical activity can help enhance cancer survival. Ibrahim and Al-Homaidh (2011) conducted a meta-analysis examining the association between physical activity and breast cancer outcomes. The researchers found that for women with a body mass index of < 25 kg/m^2, level of pre-diagnosis physical activity was inversely related to cancer mortality. Post-diagnosis physical activity also had an inverse relationship with mortality in all women, with the strongest effects seen in those women with a body mass index of ≥ 25 kg/m^2.

Finally, physical activity appears to be effective for the prevention and management of osteoporosis; a condition that can be debilitating and may lead to life-threatening fractures. Physical activity that is load-bearing (e.g., resistance training) or high-impact has been consistently shown to build bone mineral density (Warburton et al., 2006). Wolff and colleagues (1999) conducted a meta-analysis of the effects of physical activity trials on bone mass in pre- and post-menopausal women, and reported that these programs prevented or reversed 1% of age-related annual bone loss.

Psychological Benefits

In addition to clear benefits to physical health, regular physical activity is related to a variety of positive psychological outcomes. Among the most extensively studied and reviewed of these relations is that between physical activity and depression. Several longitudinal observational studies and randomized controlled trials have found exercise training to be effective for the prevention and management of depression, with some findings indicating it may be as effective as pharmacological treatment for individuals with major depressive disorder (Ströhle, 2009). For example, in a 23-27 year follow-up of the Harvard Alumni Study, researchers found that increased time spent in sports or leisure-time physical activity was associated with a decreased incidence of depression (Paffenbarger, Lee, & Leung, 1994). In a randomized controlled trial conducted by Blumenthal and colleagues (2007), the researchers assigned sedentary individuals over the age of 40 who had been diagnosed with major depressive disorder to one of four groups: supervised aerobic exercise (n=51), home-based aerobic exercise (n=53), sertraline (a common pharmaceutical treatment for depression; n=49), or placebo-control (n=49). The researchers found that following the 16 week study period, all three groups had substantially higher remission rates relative to the placebo control, and the groups were not significantly different. Meta-analytic evidence supports these findings as well. Results synthesized from 11 studies of individuals with depression yielded an effect that was very large (g = 1.39) favoring those that participated in physical activity relative to control (Stathopoulou, Powers, Berry, Smits, & Otto, 2006). With regard to the reduction of state and trait anxiety, studies have shown positive, albeit less robust, effects for physical activity. In a three part meta-analysis, Petruzzello et al. (1991) reported a small effect for aerobic physical activity on overall anxiety (d=-.24), which was similar for acute (d=-.23) and chronic (d=-.25) activity. The effects on state anxiety mirrored other known reduction techniques (e.g., relaxation). For trait anxiety, exercise programs were successful when they were greater than 10 weeks in duration, and individuals exercised for at least 21 minutes at a time.

Physical activity has also been shown to positively influence health-related quality of life (HRQOL) in both healthy and clinical populations. With increasing age or the development of a chronic condition, maintaining quality of life often takes precedent over increasing one's lifespan (Rejeski & Mihalko, 2001). However, as the work described above illustrates, physical inactivity has been associated with a variety of debilitating diseases, leading invariably to compromised quality of life. The literature examining the relationship between physical activity and HRQOL is substantial, indicating that the relationship is favorable. In a meta-analysis synthesizing data from 36 studies, Netz et al. (2005) reported a moderate effect for physical activity intervention on HRQOL, and this effect was three times greater than that obtained from individuals in control conditions (d = .24 and d = .09 respectively). Moderate intensity activity was the most beneficial (d = .34), as was aerobic activity (d = .29). Interestingly, several authors have found that physical activity may have an indirect effect on HRQOL, acting instead on more proximal outcomes such as self-efficacy, self-esteem, and positive feeling states. These proximal outcomes likely have a direct influence on components of HRQOL, such as physical function and mental status (McAuley & Morris, 2007; McAuley et al., 2007, 2013; Netz et al., 2005; Rejeski & Mihalko, 2001).

Cognitive Function

In recent decades, researchers have utilized a variety of advanced measurement techniques to investigate the relationship between physical activity and cognition. This area of research has been met with enthusiasm, as physical activity appears to offer a low-cost and highly accessible method for enhancing and maintaining cognitive function across the lifespan. Much of this work has focused on older adults in the interest of protecting against age-related cognitive decline (McAuley, Kramer, & Colcombe, 2004; Salthouse, 2009). In a landmark study conducted by Spirduso and Clifford (1978), older adult racquet sportsmen and runners were compared with sedentary older adults and sedentary young adults. The researchers noted that the older athletes were comparable to the young cohort and performed significantly better than the older sedentary individuals on measures of simple reaction time, choice reaction time, and movement time. In recent years, evidence from randomized controlled trials indicates that engaging in aerobic fitness training results in growth of important brain regions associated with executive functions (i.e., working memory, reasoning, cognitive flexibility, planning and coordination, and inhibition), and memory. These results are particularly intriguing, as these are the brain regions that demonstrate the greatest losses with age (Colcombe et al., 2006; Erickson et al., 2011; McAuley et al., 2004). Colcombe et al. (2006) presented data from 59 healthy older adults who were randomly assigned to receive a six month aerobic walking or non-aerobic stretching and strengthening program. Those older adults who participated in the aerobic exercise program had increased gray and white matter volume in the prefrontal and temporal cortices; regions associated with executive functioning. These findings support earlier meta-analytic results presented by Colcombe and Kramer (2003), who found that physical activity training had a positive effect on overall cognitive functioning in older adults (g = .48), and these changes were most pronounced in areas associated with executive functioning (g = .68). Studies that combined aerobic exercise with resistance and stretching exercise had greater effects than aerobic exercise alone (g = .59 and g = .41 respectively), and the greatest effects were seen in studies implementing exercise sessions of at least 30 minutes (g = .61). Another important structure that is particularly susceptible to age-related decline is the hippocampus, and these declines are often associated with memory impairment (Erickson et al., 2011; Raz et al., 2005). Erickson and colleagues (2011) reported findings from a yearlong exercise program in which older adults engaged in a walking program or a stretching and strengthening control program. Individuals who received the walking intervention showed enhanced spatial memory and increased hippocampal volume of 2%, which represents a reversal of one to two years of age-related loss.

A small but growing body of evidence suggests that physical activity may exert a beneficial effect on cognition in children. For example, Hillman and colleagues (2014) delivered a 9-month after-school exercise program to children aged 7-9 years. Those who enrolled in the program were randomly assigned to an exercise condition or a wait-list control. Following the intervention period, those in the intervention condition demonstrated increased aerobic fitness, enhanced amplitude of the P3 component of the event-related potential (reflecting increased attentional resource allocation to the task at hand) and P3 latency (reflecting faster processing speed), and improved performance on heterogeneous (i.e., more difficult) tasks of cognitive flexibility and inhibition. These results reflect those of a review focusing on neuroelectric outcomes of physical activity participation in children (Hillman et al., 2011). The authors reported that higher fit children show increased P3 amplitude, decreased P3 latency, and decreased amplitude of the ERN component, which is thought to correspond with more efficient action monitoring. Additionally, higher fit children are better able to modulate the amplitude of these components. The authors concluded that lower fit children appeared to rely on more heavily action monitoring strategies while completing cognitive tasks. These strategies may not adequately meet the demands of more challenging tasks, resulting in poorer performance. Higher fit children, on the other hand, appear to modulate their attention and action monitoring to meet the demands of the task, thus maintaining performance across tasks. Finally, meta-analytic evidence also appears to support a positive association between physical activity and cognition in this population. Sibley and Etnier (2003) synthesized the results from studies pertaining to physical activity and cognition in children. The analysis yielded a small to moderate overall effect (g = .32), indicating a significant positive relationship between activity and cognition in children.

Though much work remains to be done to understand the underlying mechanisms driving the relationship between physical activity and various domains of health, the benefits of the behavior are clear and abundant. These benefits, however, are predicated on motivating the individual to become active and to remain so. The next section explores the use of Albert Bandura's social cognitive theory (1986, 1997) to understand and influence physical activity behavior.

The Use of Social Cognitive Theory in the Study of Physical Activity Behavior

Overview of Social Cognitive Theory

Despite the many health benefits of physical activity, rates of global physical inactivity are astounding. It is a complex and dynamic behavior wrought with disincentives and impediments (e.g., dislike for intense physical exertion, perceived lack of time; Bandura, 1997; McAuley, 1993). In an effort to better understand the antecedents and consequences of physical activity behavior, researchers have turned to behavioral theories to design and evaluate their interventions. One theory that has been used with success across many behaviors is social cognitive theory (SCT; Bandura, 1986, 1997). Social cognitive theory is founded on *triadic reciprocal causation* (i.e., reciprocal determinism) whereby personal (i.e., cognitive, affective, and biological events), environmental, and behavioral factors all interact with one another (see Figure 3; Bandura, 1986, 1997). In this view, behavior is a dynamic process in which an individual has personal agency, and their behavior is partially, though not fully determined by the environment. In sum, the behavioral constructs that predict behavior in SCT are *self-efficacy, outcome expectations, sociostructural factors*, and *goals* (see Figure 1).

Self-Efficacy

Self-efficacy plays a vital role in the adoption and maintenance of physical activity behavior (McAuley & Blissmer, 2000; McAuley, Jerome, Elavsky, Marquez, & Ramsey, 2003; McAuley, 1993). Efficacy beliefs are conceptualized as one's perceptions of their ability to successful bring about a specific course of action. Those who have built a resilient sense of self-efficacy are more likely to adopt and maintain a behavior, to set and achieve more challenging goals, and to persist in the behavior despite failures, setbacks, and barriers to action. Individuals draw upon four sources of information in order to form beliefs about their personal efficacy. *Enactive mastery experiences* are believed to exert the greatest influence on one's sense of efficacy, as they provide the most direct assessment of one's ability to meet the requirements of a task. The accumulation of successes builds a resilient sense of efficacy over time; however failure, especially when encountered early in behavioral attainment, undermines efficacy beliefs. A resilient sense of efficacy is built upon overcoming obstacles and challenges, allowing the individual to feel more confident and able to persist throughout subsequent difficulties. Importantly, it is not merely success or failure that drives efficacy beliefs, but rather the individual's perceptions of the value of those successes and failures (Bandura, 1986, 1997).

Following *enactive mastery experiences*, *vicarious experiences* (i.e., social modeling) exert the next greatest influence on efficacy beliefs. That is, individuals who witness a similar person succeed in a behavior are likely to feel more capable of success themselves. In the event that the same individual fails, despite clearly exerting great effort, one is likely to have diminished efficacy beliefs. The magnitude of this effect is modulated by the degree to which one is able to relate to the model. Further, this source of information is particularly influential when an individual is highly uncertain about their own capabilities (Bandura, 1997, 2004).

Verbal persuasion (i.e., social persuasion) is yet another means of influencing one's efficacy beliefs. This source of information encompasses the degree to which significant others express faith in, or doubts about, one's ability to successfully engage in a behavior. Though perhaps less influential than mastery experiences and vicarious experiences, those who receive positive verbal persuasion are more likely to exert greater effort and persist in the behavior. Finally, one's *physiological and affective states* may have an influence on their self-efficacy. Individuals may assess aversive physiological states (e.g., fatigue, shortness of breath) or emotional states (e.g., anxiety) as indicative of their abilities, subsequently lowering personal efficacy. This effect, however, is mitigated via mastery experiences in which an individual is successful despite those physiological or emotional responses. Accordingly, this may be a more important source of information early in the behavioral adoption process (Bandura, 1997, 2004).

Self-efficacy's influence on behavior is both direct and reciprocal such that those with higher self-efficacy will be more likely to engage in a behavior, while engaging in a behavior will positively impact self-efficacy (McAuley & Blissmer, 2000). Still, efficacy is not the only important construct in the social cognitive framework. It also interacts with *outcome expectations, goals,* and *sociostructural factors* to influence behavior indirectly (Bandura, 2004). For example, a highly efficacious individual will be more likely to set and meet more challenging goals, and achieving these goals provides a salient sense of mastery, thereby reinforcing efficacy beliefs. These individuals will also hold more positive expectations for the outcomes of the behavior, and will feel more able to overcome barriers and impediments to becoming physically active, thus influencing their behavior (Bandura, 2004). More information on each of these important factors follows.

Outcome Expectations

Outcome expectations reflect the belief held by an individual that a behavior will produce a given set of outcomes, and these beliefs are comprised of three specific subdomains: Physical, social, and self-evaluative outcome expectations (Bandura, 1997; King, 2001b; Williams, Anderson, & Winett, 2005; Wójcicki, White, & McAuley, 2009). Within each of these domains, positive expectations serve as incentives for behavior, while negative expectations serve as disincentives. Physical outcome expectations pertain to the sensory experiences that accompany the behavior. In this instance, physical and sensory pleasures are incentives while pain and discomfort act as disincentives. Social outcome expectations relate to the evaluation of the behavior by others. Expecting others to react with approval, interest, or recognition, for example, incentivizes the behavior, while expecting rejection, social disapproval, or disinterest will act as a disincentive. Finally, self-evaluative expectations pertain to feelings of self-worth or satisfaction that one believes may accompany a behavior (Bandura, 1997). As was previously noted, these expectations mediate the indirect relationship between self-efficacy and physical activity. Outcome expectations also influence the types of goals set by an individual (Bandura, 2004).

Goals

Goals are an important component of SCT, serving to guide progression and effort directed toward a behavior. It is important, however, that goals are well structured and are of high quality. Process goals, which pertain to aspects of a behavior that fall directly under the control of the individual (e.g., duration, intensity and type of activity) are more effective for promoting behavior than are outcome goals (e.g., improving one’s physique). Moreover, it is important for individuals to set both long term (i.e., distal) and short term (i.e., proximal) goals, and that these are set within specific time frames. Long term goals (e.g., meeting recommendations for physical activity within six months) serve to guide overall behavior, while short term goals progress the individual toward the long term goal. Proximal goals are most effective when they are very specific, challenging but attainable, and progressive (Bandura, 1997).

Sociostructural Factors

Sociostructural factors are the final construct in the social cognitive framework. In essence these are the social and environmental facilitators and barriers to action. Among healthy adults, common barriers to physical activity include weather-related concerns, perceived lack of leisure time, lack of motivation, lack of transport, and insufficient funds to engage in an activity (Chinn, White, Harland, Drinkwater, & Raybould, 1999; Salmon, Owen, Crawford, Bauman, & Sallis, 2003). Though they do not exert a direct influence on behavior, they do interact reciprocally with both goals and self-efficacy. Put another way, individuals measure their efficacy beliefs against their perceived ability to overcome their barriers to action, while overcoming or reducing those barriers may enhance efficacy beliefs (Bandura, 2004).

Social Cognitive Theory in Physical Activity Interventions

Several researchers have employed the social cognitive framework in the design and evaluation of their interventions. Unfortunately, although the social cognitive framework is well-described by Albert Bandura, much of the work employing this framework has focused exclusively on self-efficacy. Accordingly some have called for increased work implementing the framework as a whole (Young, Plotnikoff, Collins, Callister, & Morgan, 2014). There are several exemplary interventions that employ a more comprehensive examination of SCT. For instance, McAuley and colleagues (2012, 2013) utilized DVD technology to deliver a 6-month exercise intervention to community dwelling older adults. Regular support calls served as verbal persuasion to enhance self-efficacy beliefs. Information from these calls, in addition to data obtained from exercise logs, was used to construct monthly individualized feedback, which emphasized mastery experiences. Age matched models were used in the filming of the DVDs to promote efficacy via vicarious experience, and a handbook was provided that discussed overcoming barriers and realistic outcome expectations. This program was successful in enhancing physical function, quality of life, and physical activity over the course of the intervention, and increases in physical activity and physical function were maintained after six months without researcher contact (Fanning et al., 2015; Gothe, Wójcicki, et al., 2014; McAuley et al., 2012, 2013; Wójcicki et al., 2014). This same design was also successful for increasing physical function among individuals with multiple sclerosis (McAuley et al., 2015).

In a recent systematic review and meta-analysis, Young and colleagues (Young et al., 2014) synthesized the results from 44 physical activity studies that explicitly tested the SCT. The authors found that SCT explained 31% of the overall variance in physical activity behavior. Importantly, many of the studies were of low methodological quality. Within those that were of higher quality, SCT explained a greater proportion of the variance. Both self-efficacy and goals had the most robust association with physical activity behavior, further underscoring their importance in the model. As expected, sociostructural factors were not directly associated with behavioral outcomes. Outcome expectations were also not directly associated with physical activity behavior; however, the authors note that these expectations are more effective predictors of behavior with increasing age. Participant ages ranged from 9-80 years, potentially influencing these findings.

Interestingly, despite the tremendous support for the role of self-efficacy across health behaviors, several physical activity researchers have found decreases in self-efficacy across an intervention period. McAuley and others (1998, 2011) postulated that low-active individuals may not have a reliable basis on which to estimate their efficacy beliefs. Therefore, baseline assessments of self-efficacy may be artificially inflated. To examine this phenomenon, McAuley et al. (2011) measured three domains of self-efficacy (i.e., barriers self-efficacy, self-efficacy for exercise, and self-efficacy for walking) in individuals who were randomized into a one year exercise program. Assessments were conducted at baseline, after three weeks, mid-program (i.e., month 6), and at the end of the program (i.e., month 12). When examining baseline to post-intervention, barriers self-efficacy and self-efficacy for exercise had negative trends. Upon further examination, the researchers found that individuals reported a sizable decrease in these domains of efficacy during the third week of the intervention, likely reflecting a recalibration of efficacy beliefs. By mid-program, ratings for these domains of efficacy had increased significantly. Upon completion of the one year intervention, however, efficacy levels returned to levels below those assessed at baseline (McAuley, Mailey, et al., 2011).

These findings highlight the intricate and complex nature of efficacy beliefs and their relationship with physical activity behavior. They have a strong influence on the types of behaviors we participate in, and they are dynamic and malleable. For inactive individuals newly beginning a physical activity regimen, artificially inflated efficacy beliefs may suffer as the individual is introduced to the difficult nature of the activity. This presents an important point of intervention, as the most vulnerable individuals may need intensive behavioral support to boost efficacy and avoid behavioral relapse. Those that are able to persist will find that well-designed activity programs will provide frequent mastery experiences and supportive environments, and will teach effective goal setting while fostering of realistic and positive outcome expectations, ultimately enhancing self-efficacy for physical activity behavior. However, individuals approaching the end of a structured intervention may find that they are less confident in their ability to continue the behavior without the continued support of research staff. Indeed, long-term maintenance of the behavior beyond the end of the intervention continues to be a problem for physical activity researchers (Fjeldsoe et al., 2011; McAuley, Lox, & Duncan, 1993).

In an effort to provide intensive intervention content that can be delivered in the real-world, perhaps when it is most needed, some researchers have turned toward popular consumer technologies to deliver their health behavior programs. The next section discusses the use of these technologies to create and deliver highly dynamic intervention designs that can be carried on the person at all times.

The Use of Internet and Mobile Technology in Physical Activity Research

Two terms denoting various forms of technology-driven health initiatives will be used throughout this section. *eHealth* (i.e., electronic-health) has been used broadly and has been ascribed many meanings. For the purposes of this review, eHealth will be used to describe computer and internet-delivered health materials (Eysenbach, 2001). A subcategory of *eHealth*, *mHealth* will refer to health materials delivered specifically via mobile and wireless technologies (WHO, 2011b).

As recently as the mid-1990's, less than 15% of population of the US had access to the internet (Zickuhr & Smith, 2012). Currently, nearly 90% of the population of the US has consistent access, as does more than 40% of the global population, and these figures continue to increase ("Number of Internet Users," 2014). The potential to deliver health interventions to large populations and to reach individuals without access to traditional health programs (e.g., those with limited mobility) has made the internet an appealing platform for researchers (Davies, Spence, Vandelanotte, Caperchione, & Mummery, 2012). In a meta-analysis examining 34 internet-delivered physical activity interventions, Davies et al. (2012) found a positive, albeit small mean effect (d = 0.14) for internet-based interventions on physical activity. The authors noted, however, that results were highly variable, as was intervention design and participant characteristics. For studies that recruited only low-active individuals, the effect size was much larger (d = 0.37). The variability in outcomes is unsurprising, as internet-based study designs range from simple, static text or video presentation of information to highly complex and interactive theory-based designs. In their systematic review and meta-analysis, Webb, Joseph, Yardley, and Michie (2010) noted that eHealth interventions using behavioral theory to guide their design had larger effects on health behavior, as did those that used a greater number of behavior change techniques. Additionally, the authors noted that tailored, motivational messages (e.g., presented via text message or email) provided additional support for behavior change.

The use of mobile technologies to deliver intervention content was a logical extension to research implementing internet-based designs. Usage rates for mobile phones has increased dramatically in the last 15 years. In 2000, half of the adults in the U.S. owned a cellular phone, while 90% owned some type of mobile phone in 2014. In 2007, Apple released the first generation of their popular iPhone smartphone, and since that time, adoption of these devices has risen tremendously. Between 2011 and 2014, ownership rose from 35% to 64% across all demographics (*Device Ownership Over Time*, 2014). Presently, approximately 90% of those aged 25-34 own a smartphone, and three in four adults own a smartphone in each age group between 13 and 54. Among the oldest populations, ownership rates are rising dramatically such that half of those aged 65 and older now own smartphone devices (ComScore, 2015).

Mobile phones offer a number of unique advantages to the researcher: they are widely used and tend to be carried at all times by their owners, and they provide the ability to interact with individuals in real time via text messaging, push notifications, and email. Smartphones hold additional advantages, as they contain a number of sensors that allow researchers to measure geographical location via GPS and physical activity via accelerometer. Smartphones provide access to the internet in nearly any location, and are easily able to run sophisticated and interactive programs (Dufau et al., 2011; Fanning et al., 2012; Miller, 2012). A number of reviews have been conducted to examine the ability of mobile devices (e.g., mobile phones, smartphones, personal digital assistants) to influence physical activity behavior (Fanning et al., 2012; Muntaner, Vidal-Conti, & Palou, 2015; Stephens, Allen, & Rn, 2013). In one review and meta-analysis, Fanning et al. (2012) identified 11 studies comprising 1,351 individuals that utilized mobile devices to influence physical activity. There was a moderate overall effect (g = 0.54) on behavior. At the time of the review, the most commonly utilized feature of the device was text-messaging for the provision of tips and feedback. Though these messages may provide an efficient means of delivering theoretically guided messages, these techniques are infrequently automated, and it is unlikely that they are sufficiently robust to support long-term maintenance of behavior. The authors identified only one intervention that utilized a smartphone application, and it did so simply to allow individuals to log daily steps. In a more recent meta-analysis, Muntaner and colleagues were unable to locate additional studies with smartphone-based designs (Muntaner et al., 2015).

After publication of the initial meta-analysis, Glynn et al. (2013, 2014) conducted the SMART-MOVE intervention, which provided participants with a commercially available smartphone pedometer application (app), allowing them to view real-time step count feedback. Intervention participants were instructed to attempt to achieve 10,000 steps per day, while those randomized to the control condition were instructed to attempt to walk for 30 minutes per day. Following an eight week trial, the researchers found that users in the app condition increased daily steps, while those without the app did not. These positive results are similar to those seen in standard pedometer-only interventions (Bravata et al., 2007). Though effective in the short term, it is unlikely that the simple provision of a pedometer will support long-term maintenance of physical activity behavior (Bravata et al., 2007; Webb et al., 2010). Indeed, results of a recent review of commercially available smartphone apps serve to caution researchers against their use. Conroy, Yang, and Maher (2014) reviewed 167 top-rated commercially available fitness apps and reported that behavior change techniques were not frequently employed, concluding that an individual would need to download and use several apps simultaneously to initiate and maintain behavior.

Across technologies, there is a paucity of research implementing fully automated and tailored designs. Ritterband and Thorndike (2012) provide important commentary on the use of human support in eHealth and mHealth interventions. The authors note that current technologies allow for a continuum of human involvement in the provision of tailored content such that some require heavy input and others may be fully automated. The ability to automatically provide material that is individualized and meaningful is an important one in the context of public health, as inexpensive scalability is necessary for realizing the broad reach of the platform. Put another way, intervention designs requiring human input inherently become cost-prohibitive with the addition of participants. Though automated intervention designs are more costly at the outset due to programming and testing costs, the additional cost per participant is negligible. Accordingly, such programs are more likely to be implemented beyond the research context. Though rare, several eHealth programs have successfully made this transition. For example, Ritterband and colleagues (2009) developed an internet-based program to deliver treatment based on cognitive behavioral therapy for insomnia (CBT-I). Individuals were assigned to the intervention group or to a wait-list control. The intervention condition received treatment content in the form of text, graphics, vignettes, quizzes, and games. Participants also completed regular sleep diaries and received individually tailored sleep restriction recommendations. Following the nine week intervention period, intervention participants significantly reduced the severity of their insomnia while the control condition did not, and these effects were maintained after a six month follow-up period. Additionally, the intervention group had a significant decrease in wake after sleep onset (WASO), and a significant increase in sleep efficiency relative to the control condition. Currently, this program is used broadly by a number of respected hospitals and sleep institutes.

The MOST Framework for Building and Evaluating eHealth Interventions

Despite the popularity of smartphone devices, the lack of published findings utilizing well-designed, theoretically-driven applications is to be expected, given the time required to conceptualize, fund, conduct, and publish traditional randomized controlled designs. Some estimates place the average length of this cycle at seven years (Glasgow et al., 2014; Riley et al., 2013). This stands in contrast to the speed with which consumer technologies develop. By this timeline, a study published in 2014 was likely conceptualized as Apple's first generation iPhone was released. Upon completion of this long process, researchers conduct post-hoc analyses of the intervention and its components to attempt to understand which are most effective, and then new research questions are formed and the cycle is renewed. In this way, the researchers often hope to move slowly toward an optimized intervention design. In the context of eHealth interventions, this process is far too slow (Collins et al., 2005, 2007). To promote the efficiency of this process, a variety of alternative methods for more rapidly building and evaluating eHealth interventions have been proposed. The multiphase optimization strategy (MOST) is one such framework that was adopted from engineering practices and has received a fair amount of attention (Collins et al., 2005).

The MOST approach aims to accomplish both the optimization and evaluation of behavioral interventions simultaneously and in a much abbreviated manner. This is accomplished in three phases: The *preparation* phase places emphasis on theory to select important intervention components that merit investigation. During this phase, researchers often utilize factorial designs (Collins, Dziak, et al., 2014; Montgomery, Peters, & Little, 2003) to test these intervention components. This offers several important advantages over standard RCT methods. Most importantly, factorial methods allow researchers to test the efficacy of each intervention component as well as their interactions, while substantially reducing the number of participants that would be required to power an equivalent set of RCTs (Collins et al., 2005, 2007). During the subsequent *optimization* phase, effective elements are retained from the preparation phase, and dose, intensity, and frequency of each component are manipulated. Once again these are tested using a factorial design. The *confirming* phase serves to test the final intervention containing the most effective components at the optimal levels in a standard RCT design (see Figure 2). Researchers may then make more acute statements based upon individual intervention components and their interactions, and are not bound to make statements about the intervention package as a whole (Collins et al., 2005).

It is not uncommon for authors to call for the use of MOST and similar frameworks as future directions for the field of health behavior (e.g., Birch & Ventura, 2009; Danaher & Seeley, 2009; Irvine et al., 2010; Kumar et al., 2013). However, perhaps due to its relative novelty, the framework has seen little use outside of the realm of smoking cessation (Strecher et al., 2008).

Recent reports indicate the first designs targeting physical activity are currently in development (e.g., Buman et al., 2015). These designs are particularly important for mHealth researchers for a number of reasons: first, the experimental procedures are rigorous, allowing researchers to remain true to the scientific process, in turn leading to the development of effective, theoretically-derived mHealth intervention techniques. As these techniques are evaluated and disseminated, they may serve to guide an active commercial sector that is largely lacking in evidence-based programs. Additionally, by evaluating components individually and in combination, researchers can apply techniques across technologies. Standard RCT designs allow researchers to test a program as a package, but this information becomes less meaningful as technologies advance (Collins et al., 2007). With the use of the MOST framework, individual techniques deemed effective within internet-based interventions can reasonably be adapted to the smartphone platform, and then to newer popular technologies as they emerge.

Summary

At the present time, a great deal of work has set the stage for the effective use of mHealth technologies in physical activity interventions. The evidence suggests that highly tailored, automated, theory-driven designs should be effective for supporting the initiation and maintenance of physical activity behavior. Moreover, roughly two in three American adults carry with them a device that allows for the delivery of just this type of intervention content. Finally, both theoretical and analytic frameworks (e.g., social cognitive theory, multiphase optimization strategy) exist that serve to guide the rapid development and evaluation of these programs. The purpose of the present study was to capitalize upon these future directions to deliver a tailored and automated physical activity intervention via the smartphone that is nested within the *preparation* phase of the MOST framework. The next section describes the methods for this study.

Chapter 3: Methods

Participants

Healthy, low-active adults (*N* = 116; aged 30-54 years) were recruited from Champaign-Urbana and surrounding communities to participate in a 12-week exercise study. As recruitment was conducted primarily within a university community, a minimum age of 30 was selected to focus recruitment efforts away from college-aged adults. Additionally, recent statistics indicate smartphone ownership rates are greater than 75% across all age groups from 13-54 years, dropping to 64% among adults aged 55-64,and 49% for those aged 65 or older (ComScore, 2015); therefore, 54 years was selected as a maximum age to reduce the potential for sampling bias. Recruitment was conducted via printed flyers, listserv announcements, and social media advertisements. Interested individuals contacted the research staff via online form, email, or telephone, and then participated in a screening telephone call to be assessed for interest and eligibility. Those who were interested and eligible were scheduled for an orientation session as described below.

Inclusion and Exclusion Criteria

Adults who met inclusion criteria for this study were aged 30-54 years, low active (i.e., not engaging in 30 or more minutes of moderate to vigorous activity on two or more days per week), the owner of an iPhone or Android smartphone with consistent access to text messaging and mobile internet for the duration of the study, and willing to be randomized to any research condition. Exclusionary criteria include an inability to communicate in English, presence of cognitive impairment as assessed by the Modified Telephone Interview for Cognitive Status (de Jager, Budge, & Clarke, 2003), inability to walk without assistance, or any medical contraindication to physical activity participation.

Experimental Design

The present study was nested within the first phase (i.e., the *preparation* phase) of the MOST framework, with the aim of determining the individual and combined efficacy of two theory-based, smartphone-delivered modules designed to promote physical activity. Accordingly, the study was designed as a four-arm randomized factorial trial (see Table 2 for a graphical representation of group assignment). A detailed description of each application component follows.

The Base-Level App

All individuals in the study (i.e., groups A-D) received access to the same base-level app features (i.e., tracking, education, feedback), and individuals in group D received these components alone. These are features that are common to eHealth and print-based interventions (e.g., Glynn, Hayes, & Casey, 2014; Hurling et al., 2007), and we hypothesized they should support some level of physical activity behavior, allowing for the examination of the unique contribution of the theory-based application components.

Tracking. The first of these features provided daily physical activity logging. Individuals were instructed to log the type, intensity, duration, perceived intensity, and perceived enjoyment of any physical activity in which they engaged, and were provided the opportunity to add notes of any type to provide additional detail for the exercise bout. During preliminary testing of the study app, trial users often tracked activities at the end of the day, or on the night before the weekly feedback was generated. This process is likely to introduce recall bias (Prince et al., 2008), and in turn to impair the program's ability to give useful feedback or realistic goal recommendations. Therefore, during the orientation appointment, participants were urged to track activities immediately following the completion of the activity. Further, to promote timeliness and to reduce retrospective tracking, activities were time stamped as they were entered, and participants were unable to manually specify the date on which the activity occurred. These updates were introduced during preliminary testing, and users responded positively.

The tracking feature primarily functioned to inform the instantaneous in-app feedback and weekly email and text message-based feedback (described below). For those without in-app goal-setting (i.e., groups C and D), participants entered a brief label for each activity completed, as well as duration in minutes, and intensity and enjoyment on a five-point sliding scale. For those with in-app goal-setting, goal-related activities populated buttons that were selected by the participant once an activity was completed, and the option was provided to free-enter additional activities. See the section titled *The Guided Goal Setting Module* for more information related to in-app goal-setting, and Figure 4 for screenshots depicting group-specific tracking.

In-App Feedback. Throughout the study period, individuals maintained access to graphical feedback displaying daily and weekly physical activity duration, intensity, and enjoyment summaries. Each individual also had access to an activity "diary", which displayed detailed activity information (i.e., activity date, time, duration, and notes), as well as historical activity summaries for each week in the program. Additionally, for individuals with access to the goal setting module, this feedback displayed progress toward the weekly goal. See Figure 5 for screenshots depicting in-app feedback.

Education. All individuals were provided access to a new educational module each week. These modules included one short video (i.e., five minutes or less) discussing important concepts in social cognitive theory and health behavior (e.g., goal setting, barrier identification). Each video was paired with a very brief quiz question that was provided once an individual watched at least 75%

of the weekly video, and upon answering the quiz question, the individual received "support content" related to the theme of the week (e.g., strategies for overcoming barriers to activity). See Figure 6 for screenshots depicting the knowledge feature.

Weekly Feedback. Finally, each participant received fully automated feedback twice weekly. On each Sunday during the study period, participants received feedback via email containing a small motivational paragraph discussing the individual's position in the program, their performance within the program (e.g., whether a weekly goal was met), and the content of the weekly educational module. The email feedback also contained summary information for the week, including number of exercise sessions completed and number of minutes of exercise for the week, goal activity summaries where relevant, and average exercise intensity and enjoyment. This feedback was modeled on a successful SCT-guided PA intervention (McAuley et al., 2013). To support adherence within the week, participants also received text message-delivered feedback on each Thursday of the program. This feedback provided a brief summary of weekly activity during the first half of the week, and provided activity strategies and encouragement for individuals who had not yet logged activity for the week (e.g., "be sure you are spreading your activities throughout the week and tracking as you go!"). See Figure 7 for screenshots depicting email-delivered feedback.

The Point-Based Feedback Module

Because high self-efficacy for engaging in an active lifestyle is vital for doing so, the web app implemented novel methods for delivering instant feedback and incremental rewards. This was accomplished using a system of "program points" (*pp*), "levels", and "badges". For individuals randomly assigned to groups A or C, every component of the web app was associated with a number of *pp* weighted by importance or difficulty of the task. For example, logging aerobic exercise for the day earned the participant 10 *pp*. Viewing a weekly educational module for the first time was worth 10 *pp* and answering the easy follow-up question resulted in 5 additional *pp*. For individuals randomized to group A, who therefore had access to the guided goal-setting component of the app, setting and achieving physical activity goals resulted in incremental *pp* rewards. See Table 3 for a detailed description of point allocation.

Earned *pp* were depicted as a percentage on a status bar at the bottom of the home screen, and a level was earned once the participant earned enough *pp* to fill the bar. Levels were provided quickly at the start of the program, and more slowly over time in accordance with the following linear rising level gap formula, using a constant of 10:

$$Points\ Required\ per\ Level = \frac{level^2 + level}{2} * constant - (level * constant)$$

Put another way, each level required the number of points needed to earn the previous level, plus ten points. Accordingly, the individual began the study at level one with zero points. By logging one activity, the individual received the 10 points required to earn the second level. The third level then required 20 additional points for a total of 30 points, the fourth required 30 additional points for a total of 60. In intervals of five levels, individuals were awarded a new title and badge that was accompanied by brief motivational information. Participants began the program with the title "Rookie Exerciser" and a badge depicting a comical, stylized character. At the fifth level, the individual received a badge depicting their character becoming increasingly fit. On reaching level ten, they were informed that they were now a level 10 "Apprentice Exerciser", and received another badge depicting the character becoming still more physically fit. Throughout the remainder of the program, badges were provided in five-level increments, and titles every tenth level. These were intended to provide incremental, positive feedback that consistently acknowledged both goals and mastery experiences as participants moved through the program. Detailed information pertaining to levels, points, titles, badges, and motivational passages is provided in Table 4, and an example screenshot depicting the “Points” screen can be seen in Figure 8.

The Guided Goal Setting Module

In addition to the points-based feedback module, this study aimed to test the efficacy of a guided goal-setting module. During the program orientation, staff provided all participants with counseling on a goal setting process that incorporated SMAART Goals principles (i.e., Specific, Measurable, Action-Oriented, Adjustable, Realistic, Timely) and goal-setting procedures described by Bandura (1997). The purpose of these goals was to guide the individual toward achieving public health recommendations for physical activity over the course of the 12 week intervention. To accomplish this, two distal goals were first selected: one goal targeted aerobic activity, and reflected the total amount of weekly activity that participants aimed to achieve within the study period (e.g., 30 minutes of moderate to vigorous aerobic activity on 5 days per week). Then, a second activity-related distal goal was set emphasizing strengthening and other non-aerobic activity (e.g., do 30 minutes of moderate to vigorous strengthening exercises twice per week). Participants were provided the public health guidelines for physical activity as a starting point, and discussed customizing the recommendations to ensure each distal goal was challenging but attainable. The participant was then be asked to set the first proximal goal for each distal goal (e.g., “For the next week, I will jog, swim, or cycle at a moderate intensity on 3 days for 15 minutes each day). For these proximal goals, individuals selected between two and three specific activities that were accessible and were able to be done either inside or outdoors. Participants were also provided several reputable exercise resources (e.g., the American Council on Exercise activity library), and were advised to select and experiment with new activities throughout the program to identify those that were most enjoyable.

Individuals assigned to groups A and B had access to the goal setting module within the app. Accordingly, the app guided these participants through the process of entering their proximal and distal goals into the module, and the first set of goals were set under the supervision of the research staff. During the week, as the individual tracked goal-related activities, the module displayed their progress toward their goal (i.e., the number of bouts of aerobic and non-aerobic goal activities accomplished, and the total number needed). When an individual met a proximal or distal goal, an alert containing a congratulatory message was triggered, and the individual was given the opportunity to set new goals at the start of the following week.

On each Sunday of the program, MAPS once again guided the individual through the process of revising their goals. Participants were unable to edit long-term goals until they were met, at which point they were able to either increase or maintain their desired frequency and duration of the activity. Short term goals were set each week such that individuals received minimum, maximum, and recommended frequencies and durations based upon goals that were previously met and their position within the program (i.e., duration was prioritized in early weeks, frequency was prioritized in later weeks). For instance, if an individual failed to meet their first goal, they were able to reduce their goal duration or frequency at the start of the next week. Once a goal was met successfully, the individual was unable to set a goal below the previously-met successful goal, with one exception: Once an individual exceeded 30 minutes per session of activity, they remained able to set a goal duration of 30 minutes (i.e., a maintenance goal) to avoid overly challenging or unrealistic goals. Similarly, an individual was never required to set an aerobic goal of greater than five days per week or a non-aerobic goal of greater than two days per week. The individual was also unable to set goals outside of the recommended minimum and maximum frequency and duration to avoid unrealistic goal progression. As short-term goals were met, this window slowly increased each week until the individual accomplished their distal goals. This hierarchical structure breaks down difficult behaviors (e.g., engaging in 150 minutes of aerobic physical activity each week) into specific and easily accomplished goals. A complete ruleset that guided the goal-setting algorithm is provided in Table 5.

Individuals without access to the goal setting module (i.e., those in groups C and D) received a printed goal-setting handbook, and were advised to place the handbook in a visible location. This handbook contained all of the functions of the goal-setting module, allowing the individual to set proximal and distal SMAART goals for aerobic and non-aerobic activities. Each individual retained access to the handbook, allowing for monitoring of progress toward each weekly goal, and a sufficient number of pages were provided to allow the individual to set up to six distal goals, and 12 weekly proximal goals. See Figures 9 and 10 for screenshots depicting the goal setting module and the goal-setting handbook utilized by those without access to the module.

Physical Activity Intervention

Each participant received a progressive home-based physical activity program adapted from the federal physical activity guidelines (U.S. Department of Health and Human Services, 2008). As described previously, all participants were instructed during the initial orientation appointment to set an initial distal goal of engaging in five days of moderate intensity aerobic activity (i.e., 64-76% of age-predicted maximal heart rate; Garber et al., 2011) totaling 150 minutes per week. An additional distal goal related to non-aerobic activity was set such that individuals would aim to engage in moderate muscle strengthening and/or flexibility exercise twice per week for at least 30 minutes per session. For individuals with access to the guided goal setting component, these were entered into the study app, while the remaining participants entered their proximal and distal goals into a printed goal setting notebook.

To facilitate progression, all participants were then advised on setting and revisiting their proximal goals on a weekly basis in accordance with SMAART goals principles. All participants received weekly feedback on their performance during the previous week, and this feedback pressed each participant to revisit their goals. Those with access to the goal-setting module received specific feedback relative to their success and failure in meeting the goal, and received proximal goal recommendations that moved them toward their distal goal following a successful week, or that facilitated goal revision following an unsuccessful week.

Study Sequence

All participants who responded to recruitment efforts were screened by telephone for eligibility. Basic demographic information was collected during this initial phone call. Those who were eligible and agreed to participate were first entered into the study software suite. On adding an individual to the study system, a trial text message was sent the participant smartphone, which contained a link that allowed the individual to set a study password. This process verified that the participant's carrier allowed for study text message delivery, and the participant's phone was sufficiently capable of accessing the web-based study materials. Next, participants received access to an Institutional Review Board approved digital informed consent document and web-based baseline questionnaires. Additionally, each individual received an activity monitor via postal mail, and were instructed to wear the monitor during waking hours for one week prior to the orientation appointment.

Following the phone call, individuals were randomly assigned to one of the four intervention conditions based upon the order in which they were screened such that two individuals were assigned to each group in a rolling fashion. Orientation sessions were conducted in the Exercise Psychology Laboratory in which participants met in small groups to receive information on study aims, goal-setting, activity selection, and what to expect from the twice-weekly feedback. Individuals were then split into groups based upon randomization. During these smaller group-specific meetings, the individual's version of the application was added to their phone, they were introduced to each available application feature, and initial goals were set.

The 12-week intervention component began on the Sunday of the following week. During the 11th week of the study, participants again received the activity monitor in the mail, and were instructed to wear the device during the final week of the study. Upon completion of the intervention, participants received the online questionnaires one last time, and were scheduled for a very brief follow-up appointment. During this time, participants returned activity monitors and completed a short feedback survey. Following completion of these procedures, all participants received a $15 gift card to a national retailer.

Study Software Suite

All aspects of the web application suite were developed for this study by the researcher (JF) using a combination of Perl, PHP, HTML, CSS, and JavaScript, and the suite was hosted on a commercial platform operated by Netfirms Incorporated. All emails were generated automatically by the program and sent via the study server, as were study text messages, which were sent to the individual via a commercial SMS platform (i.e., Twilio) using a local, study-specific telephone number. All study webpages were protected via transport layer security (TLS) protocol, and all data were encrypted prior to storage.

Participants completed study questionnaires within the study portal. Answers to each questionnaire were saved as the user progressed, allowing the individual to leave and return to the questionnaires at another time. Additionally, all item responses were validated in real time to check for missed items, or values that were not within reason (e.g., sitting for more than 1440 minutes per day). Out-of-range values required an individual to revisit the item, and skipped items required the individual to explicitly indicate whether they intended to skip the item or not, and intentionally skipped items were coded as such.

The intervention application was developed as a web app, and accessed from user smartphones via Safari on iPhone devices, or Chrome on Android devices. Both operating systems allow web apps to be saved to the user's primary home screen as an application. This process includes an icon and a launch screen, and all browser features (e.g., task bar, forward and back buttons) can be removed to provide full control of the user experience. Finally, all app materials can be loaded at once, and the program subsequently animated with JavaScript, eliminating load times often associated with websites. Accordingly, the user experience is similar to that produced by a native application, but updates are able to be delivered in real time. Web apps are also cross-platform compatible, which is an important feature for increasing the potential reach of health programs.

Measures

Baseline Demographics.

During the screening telephone call, participants were asked a series of basic demographic questions including age, gender, annual household income, race, ethnicity, employment status, and marital status.

Physical Activity

This research utilized Actigraph accelerometers (Actigraph, Pensacola, FL; Model GT1M or newer) in order to obtain an objective measure of physical activity. Participants were asked wear the device on their non-dominant hip during waking hours for seven days, and recorded the times the monitor was worn each day on a log for the purpose of verifying device wear and non-wear time. Participants wore the activity monitor for one week prior to the start of the intervention, and again during the final week of the study (i.e., week 12). Data from these monitors were processed in Actilife version 6.13.2 (Actigraph, Pensacola, FL) with an interruption period of 60 minutes, and those with at least 10 hours of wear time on at least three days were retained for analyses (Troiano et al., 2008). Next, these data were scored using cut points designed for adults, such that ≥1952 counts per minute corresponds with MVPA. Finally, average daily minutes of MVPA was calculated by dividing total minutes of MVPA by number of valid days of data.

Psychosocial Measures

Self-Efficacy. To assess efficacy for overcoming perceived barriers to being physically active, we utilized the *Barriers Specific Self-Efficacy Scale* (BARSE; McAuley, 1992), modified to reflect current recommendations to achieve 150 minutes of MVPA per week. This 13-item scale examines subjects' perceived ability to exercise five times per week for 30 minutes or more over the next two months in the face of common barriers. We also measured exercise-specific self-efficacy using the *Exercise Self-Efficacy Scale* (EXSE), and this was also modified to reflect current physical activity recommendations (McAuley, 1993). This scale assesses a participant's beliefs in their ability to continue exercising five times per week at a moderate intensity for 30 or more minutes per session for increasing periods of time. Finally, we assessed self-efficacy for engaging in daily physical activity using the *Lifestyle Self-Efficacy Scale* (LSE; McAuley et al., 2009). This scale is similar to EXSE, but rather than focusing on bouts of purposeful exercise, it assesses an individual's beliefs in their ability to accumulate 30 or more minutes of physical activity on five or more days per week for increasing periods of time. Items on all self-efficacy questionnaires asked participants to rate their confidence on a 100-point percentage scale such that 0% corresponds with "not confident at all", and 100% corresponds with "highly confident", and scale scores were generated by averaging all items in the scale. Higher scores represent greater self-efficacy.

Perceived Barriers. We measured perceived barriers to exercise using the *Perceived Barriers Scale* (Rogers et al., 2005). This 21-item questionnaire asked individuals to rate how frequently each barrier (e.g., "Lack of Company") had interfered with exercise in the last month. These ratings are provided on a 5-point scale such that 1 corresponds with "Never" and 5 corresponds with "Very Often". A total scale score was generated by summing all items, and possible scores ranged from 21-105, with higher scores reflecting a greater number of barriers.

Outcome Expectations. We assessed outcome expectations for exercise using the *Multidimensional Outcome Expectations for Exercise Scale* (Wójcicki et al., 2009). This 15-item questionnaire assesses the three dimensions of outcome expectations for exercise (i.e., physical, social, and self-evaluative). Participants were asked to rate the degree to which they agree with statements relating to outcome expectations (e.g., "Exercise will increase my muscle strength") on a 5-point scale. Three subscale scores were generated, which correspond with physical (scores range from 6-30), social (scores range from 5-25), and self-evaluative outcome expectations (scores range from 4-20). Higher scores are indicative of higher levels of outcome expectations for exercise.

Goals. Exercise-related goals were assessed using the *Exercise Goal Setting Questionnaire* (Rovniak, Anderson, Winett, & Stephens, 2002). This questionnaire assessed participants' ability to set and meet goals relative to exercise behavior by asking how closely a series of statements describes them (e.g., "I usually set dates for achieving my goals") on a 5 point scale such that 1 corresponded with "Does not Describe" and 5 corresponded with "Describes Completely". A total scale score was generated by summing all items, with possible scores ranging from 10-50 such that higher scores reflect greater goal setting behavior.

Use and Usability Measures. As maintaining long-term use of health technologies is often a challenge for researchers (Murray, 2014), several measures of application use were collected during the study period. First, application accesses were monitored by recording the date and time the application was opened from the home screen. Additionally, video access was tracked by monitoring when each person watched at least 75% of video. Unfortunately, this feature was removed by the provider (i.e., YouTube) within the final six weeks of the study period, so these data were not complete for all individuals.

Following the intervention, participants also completed a short series of Likert-type and open-ended questions assessing the acceptability of the individual features of their web app. These provided participants the opportunity to comment on favorite and least favorite features of the app, which features were the least helpful and the most helpful for becoming physically active, and which features they would like to see implemented in the future. They were also provided the opportunity to assess the ease or difficulty associated with using each available module on a 5-point Likert scale, with response options ranging from "very challenging" to "very easy". Participants were able to comment on their favorite and least favorite aspect of each module. Finally, participants were provided an open-ended opportunity to provide additional notes.

Data Analysis

Power Analysis

Power calculations were carried out using GPower 3.143 based upon recently published results from a smartphone-delivered physical activity intervention for adults (Glynn et al., 2013) that yielded a moderate effect size (Cohen's *f*) of .28. For a moderate effect on the primary outcome (i.e., MVPA as assessed via accelerometry), with an α of .05 and power of .80, a minimum of 103 participants were needed. After increasing to 104 to account for four groups, an additional 25% were sought to account for potential drop outs from the program, resulting in a total sample size goal of 136 participants. A total of 116 individuals were successfully recruited to participate.

Quality Control and Data Checking

First, all data were downloaded and imported into SPSS, version 23 (IBM Corp, Armonk, NY). The data were manually inspected to verify the online validation procedures were successful. Specifically, descriptive statics were examined for all raw and processed variables to look for missing or erroneous data. Next, missing data were imputed using the multiple imputation feature in SPSS. Finally, these data were checked for extreme outliers and Windsorized to three standard deviations when necessary.

Specific Aim 1

The primary outcome of this intervention is average daily minutes of MVPA. In order to test the effectiveness of the individual intervention components for increasing MVPA, a two-way repeated measures factorial analysis of variance (RM-ANOVA) was utilized to examine the influence of both intervention components (i.e., guided goal setting, points-based feedback) on change in average daily minutes of MVPA from study baseline to follow-up. This approach is useful during *preparation* and *optimization* phase studies within the MOST framework, as it allows for examination of the individual and combined effectiveness of each intervention component. Accelerometer-measured MVPA at baseline and week 12 were entered as dependent variables, and presence of each component (coded as -1 for absence or 1 for presence) were included as fixed factors. For each analysis, stepwise linear regression analyses were used to identify significant predictors of each dependent variable at baseline, and these were included in each RM-ANOVA as covariates. It was hypothesized that the interaction effect between time and each of the two intervention components would be significant, as would the three-way interaction between time, goal setting, and points.

Specific Aim 2

Similar analyses were conducted to examine the individual and combined influence of the intervention components on key SCT constructs (i.e., perceived barriers, goal setting, outcome expectations, self-efficacy). It was once again hypothesized that the results would reveal significant interactions between time and each intervention component for each of the key SCT constructs, as well as a significant three-way interaction term.

Specific Aim 3

App Access. Due to the longitudinal nature of the application access data, hierarchical linear modeling was used to examine weekly application accesses over the 12-week study (Hox, 2010). The analysis followed a forward-stepping hierarchical approach in which fixed and random effects of linear and quadratic time on number of accesses were first tested. Next, fixed effects of the goal setting module and the points module were included in the model. Model fit was assessed with -2 Restricted Log Likelihood, Akaike's Information Criterion (AIC), and Schwarz's Bayesion Criterion (BIC). Predictors were retained in the model at $P < .10$, and were considered significant at $P < .05$. It was hypothesized that each intervention component would lead to higher degrees of interaction with the application, with the greatest use among those with both components. Additionally, as with all technology-driven interventions, some amount of decay in use was expected, but it was expected this would be small due to the presence of individualized support (i.e., text- and email-based feedback). Accordingly, a small but significant effect for time was expected.

Post-Intervention Participant Feedback. Finally, in order to examine participant response to the app, all post-intervention qualitative feedback forms were processed in the following manner: first, to identify common themes, all feedback forms were read in full by the researcher. Next, up to three items were extracted from each open-ended question for each participant, and these were coded and entered into SPSS. Finally, descriptive statics were generated on these coded items as well as the Likert-type ease-of-use items for the full sample, and for individual groups as appropriate to identify the most commonly reported themes for each item. It was expected that all components of the intervention would be well tolerated, but that those with in-app goal setting would report more favorably for goal setting and related items (e.g., in-app feedback).

Chapter 4: Results

Recruitment, Screening, and Study Flow

Recruitment and randomization was conducted on a rolling basis between November, 2015 and February 2016. Three primary recruitment sources were used in the present study. First, paper flyers were distributed to local businesses (e.g., coffee shops, restaurants), university buildings, and community resources (e.g., churches, park districts). Additionally, two brief announcements were made via university-affiliated email listservs. Finally, paid social media (i.e., Facebook, Twitter) advertisements were placed by a community resource targeting area mothers. Of those who were able to recall their advertising source (n = 151), the university listserv reached the most individuals (n = 94), followed by paid social media advertisements (n = 45). All advertisements contained contact information for the research team, as well as the study website address. Interested individuals were able to contact the researcher by phone, email, or website-embedded form, and the researcher made a minimum of three attempts to contact each individual. Upon successfully completing the screening procedures and meeting eligibility criteria, participants were assigned to one of the four treatment conditions in rolling blocks of two individuals. For example, the first two individuals to pass screening were assigned to group A, the next two to group B, the following two to group C, and another two to group D. Participants with significant others in the study received the same group assignment. Unequal group assignment occurred when an individual passed prescreening procedures and was randomized to an intervention condition, but was later unable to complete baseline procedures (e.g., unable to come to an orientation appointment).

Ultimately, 116 eligible participants were recruited and completed baseline requirements, representing 88% of the initial recruitment goal. Of these participants, 103 completed follow-up questionnaires, 96 individuals returned activity monitors with sufficient data for inclusion in analyses, and 97 completed feedback forms. A detailed depiction of participant flow within MAPS can be found in Figure 11.

Participant Characteristics

Baseline characteristics of the 116 individuals initially randomized are displayed in Table 6. Briefly, the majority of participants (M_{age} = 41.38 $\pm$7.57) were female (80%), married (77%), white (87%), college educated (84%), and earning at least $70,000 annually (52%).

Specific Aim 1: Accelerometer-Measured Physical Activity

Initial linear regression analyses revealed education level was significantly related to activity at baseline and was entered as a covariate into the factorial RM-ANOVA. The analysis revealed a main effect for time [$F(1,103)=74.86$, $P < .01$, $\eta^2=.42$]. Examination of estimated marginal means revealed a mean increase in daily MVPA from 34.88 minutes to 46.77 minutes across the intervention, reflecting an increase of 11.90 minutes of MVPA per day across conditions (d = .70). Additionally, the analysis revealed a significant between-subjects effect for points [$F(1,103)=4.011$, $P = .05$, $\eta^2 = .04$], and estimated marginal means showed that across the intervention, those with access to the points module engaged in an additional 5.94 minutes of activity per day. No other main effects or interactions were significant (Ps > .44). See Figure 12 and Tables 7 and 8 for main effects, interactions, and means.

Specific Aim 2: Psychosocial Variables

Barriers Self-Efficacy. Linear regression analyses did not reveal any significant covariates for BARSE. The factorial RM-ANOVA identified a significant interaction effect between points and time [$F(1,111)=10.065$, $P < .01$, $\eta^2 = .08$]. Bonferonni-corrected post-hoc analyses revealed a significant decrease in self-efficacy for overcoming barriers among those without the points module (*P* < .01, *d* = -.41), and a non-significant increase among those with the points module (*P* = .20, *d* = .16). The main effects for points and goals were non-significant (*P* = .62 and *P* = .36 respectively), as were the points x goals, goals x time, and points x goals x time interactions (*P*s > .20). See Figure 13 and Tables 9 and 10 for main effects, interactions, and means.

Exercise Self-Efficacy. Again, the linear regression analysis did not reveal any significant covariates for EXSE. There was a significant main effect for time [$F(1,111)=5.269$, $P = .02$, $\eta^2 = .05$], and examination of marginal means revealed a small decrease of 5.92 percentage points across the intervention (*d* = -.19). The three-way interaction between time, points, and goals was also significant [$F(1,111)=4.250$, $P = .04$, $\eta^2 = .04$]. Again, Bonferonni-corrected post-hoc analyses revealed a protective effect for points, such that individuals with access to goal setting but without access to the points module reported a significant decrease in exercise self-efficacy across the intervention (*P* < .01, *d* = -.52), whereas those with points did not significantly change (*P* = .98, *d* = .01). Interestingly, though the trends were not significant (*P*s > .19), this pattern was reversed among individuals without access to goal setting. Among these participants, those with access to points demonstrated a non-significant decrease in efficacy over the intervention (*d* = -.29), and individuals without access to points did not change (*d* = .04). There were no other significant main effects or interactions (*P*s > .34). See Figure 14 and Tables 11 and 12 for main effects, interactions, and means.

Lifestyle Self-Efficacy. Linear regression analyses did not reveal any significant covariates for LSE. As with the other efficacy measures, the main effect for time was significant [$F(1,112)=11.860$, $P < .01$, $\eta^2 = .10$], reflecting an 8.37 percentage point decrease in efficacy across the intervention (d = -.34). No other main effects or interactions were significant (Ps > .13). See Figure 15 and Tables 13 and 14 for main effects, interactions, and means.

Goal Setting. Linear regression analyses identified race as a significant predictor of exercise goal setting strategy use such that non-white participants employed more goal strategies, and it was entered into subsequent analyses. The RM-ANOVA produced a significant main effect for time [$F(1,110)=41.285$, $P < .01$, $\eta^2 = .27$], whereby individuals across conditions demonstrated a significant 6.47 unit increase in perceived goal setting ability across the intervention (d = .80). Additionally, there was a main effect for points [$F(1,110)=7.332$, $P = .01$, $\eta^2 = .06$] such that those with the points module demonstrated greater perceived goal setting ability relative to those without points. The time x goals interaction approached significance [$F(1,110)=3.313$, $P = .07$, $\eta^2 = .03$], and post-hoc analyses revealed a larger increase in perceived goal setting ability among those with access to the goal setting module relative to those without (d = .98 and d = .63 respectively). No other effects or interactions were significant (Ps > .09). See Figure 16 and Tables 15 and 16 for main effects, interactions, and means.

Outcome Expectations. Linear regression analyses indicated that gender and annual income were significant predictors of one's score on the social outcome expectations subscale at baseline; therefore, these variables were included as covariates in the relevant analysis. With regard to the physical outcome expectations subscale, there was a significant time x points interaction [$F(1,112)=3.881$, $P = .05$, $\eta^2 = .03$], and post-hoc analyses revealed a small, non-significant decrease in physical outcome expectations among those without the points module (P = .20, d = -.19), and a small, non-significant increase among those with the point module (P = .14, d = .23). No other main effects or interactions were significant (Ps > .31). The RM-ANOVA for the self-evaluative outcome expectations subscale did not yield any significant effects, though the time x points interaction again approached significance [F(1,112)=3.166, P = .08, η^2 = .03]. As with physical outcome expectations, the examination of estimated marginal means revealed a small, non-significant decrease across the intervention among individuals without the points module (P = .37, d = -.12), and a small, non-significant increase across the intervention among individuals with the points module (P = .11, d = .23). All other effects for the subscale were non-significant (Ps > .26). The factorial RM-ANOVA for the social outcome expectations subscale did not yield any significant main effects of interactions (Ps > .08), though the main effect for time approached significance [F(1,112)=3.043, P = .08, η^2 = .03]. See Figures 17-19 and Tables 17-22 for main effects and interactions for these analyses.

Perceived Barriers. Linear regression analyses indicated gender was a significant predictor of perceived barriers at baseline, and was, therefore, entered as a covariate. The factorial RM-ANOVA revealed a significant main effect for time [F(1,111)=36.989, P < .01, η^2 = .25], such that participants reported an 8.74 unit decrease (i.e., improvement) in perceptions of barriers across the intervention (d = .84). No other effects were significant (Ps > .41). See Figure 20 and Tables 23 and 24 for main effects, interactions, and means.

Specific Aim 3: App Use and Post-Program Survey

App Accesses. Within the hierarchical linear model, the random linear effect for time was significant (B = -.17, P <.01), indicating that use decreased by approximately 0.17 accesses per week across the intervention from an initial level of 6.90 accesses per week. The fixed effect for the goal setting module was also significant (B = 1.91, P =.04) such that individuals with access to the goal setting module had approximately 1.91 additional accesses per week relative to those who did not. The fixed effect for the points module was also significant (B = 1.88, P =.04), suggesting those with access to the points module made 1.88 additional accesses per week above those who did not have access to the module. The interaction effects for time x points, time x goals, and points x goals were not significant, and were not retained in the model. See Figure 21 and Table 25 for the final model details.

Post-Program Assessment for Groups A and B. *Ease of use:* Among individuals with access to in-app goal setting (i.e., groups A and B), 58% reported that tracking goal-related activities was very easy, and another 28% reported it was fairly easy. With regard to non-goal activities, which required manual entry of an activity name, 38% reported it was very easy, 22% reported it was fairly easy, and 24% reported they felt neutral. Individuals most commonly reported they found the ease of activity entry to be the best feature of the tracking interface (n = 23), followed by its integration with in-app and weekly feedback (n = 10), and the general sense of motivation associated with self-monitoring goal-related activities (n = 5). However, participants reported a desire to retroactively track activities (n = 9) or edit goals (n = 2), and desired a social component (n = 2). When asked about in-app feedback, participants most often reported they found the graphs clear and informative (n = 20), supportive of self-monitoring (n = 11), and, in turn, motivational (n = 7). They most frequently desired more chart options (e.g., more ways to view weekly data; n = 12), and graphical feedback depicting progress throughout the program instead of within the week (n = 6).

With regard to the in-app goal setting process, 50% reported it was very easy and 22% reported it was fairly easy. The most commonly reported features enjoyed by individuals included the progressive goal structure (n = 12), the ease of goal entry and editing (n = 12), and the general motivation associated with seeing the goals in the app and in feedback (n = 9). Participants most often reported that the goal structure was too narrow (n = 20): although maintenance goals were allowed when an individual reached public health physical activity recommendations, many individuals expressed a desire to set maintenance goals earlier in their goal progression.

Favorite features: When asked about features that were the most motivating, or that helped the person to become active, the greatest number of individuals (n = 61) noted the emails and texts were the most helpful, followed by the in-app goals feature (n = 47) and in-app tracking (n = 35).

Least favorite features: The most frequently reported aspect of the app that was least motivating was the in-app feedback, which was most often related to a desire for graphs depicting progress throughout the program (n = 15), followed the need to track physical activities on the day they were completed (individuals often reported forgetting to track; n = 12), and the educational videos (n =11). It was commonly noted by these individuals that the first video was similar to orientation-appointment content, and so they did not feel inclined to watch the remaining videos.

Desired features: When asked about features that would help the individual to become or remain active, the most commonly reported was daily proactive reminders (e.g., daily feedback, reminders to track; n = 11), followed by a desire for an in-app calendar to plan out weekly goals (n = 6), and integration with commercial activity monitors or web-services (e.g., Fitbit, Strava; n = 5).

Post-Program Assessment for Groups C and D. *Ease of use:* For individuals without access to in-app goal setting (i.e., groups C and D), 51% reported that tracking goal-relate activities was very easy, while 17% reported it was fairly easy. Regarding non-goal activities, 36% reported it was very easy to enter these activities, 15% reported it was fairly easy, 19% reported they were neutral, and another 19% felt it was a little challenging. Participants most commonly reported enjoying the ease of use of the tracking system (n = 20), and its integration with feedback (n = 14), while expressing a desire to be able to retroactively track activities (*n* = 14), to find some way to integrate weekly goals into the system (*n* = 8), and to supply an activity menu for frequently-entered activities (*n* = 6). Relative to in-app feedback, participants in groups C and D often noted it supported self-monitoring (*n* = 18), was generally motivational (*n* = 6), and served as a helpful reminder to increase their physical activity (*n* = 5). The individuals in these conditions disliked the lack of integration with the goal-setting process (*n* = 11), and the lack of graphical feedback for progress across the intervention (*n* = 2).

With regard to the goal-setting process via the goal setting handbook, 15% reported it was very easy, 32% reported it was fairly easy, 21% reported they felt neutral, and 28% indicated it was fairly challenging. It was most often reported to be practical (*n* = 13), to provide structure to the planning process (*n* = 6), and to foster realistic goals (*n* = 4), but most participants desired in-app goal setting (*n* = 26), finding it easy to misplace or forget the booklet (*n* = 8).

Favorite features: Relative to features that helped the individual to become or stay active, the most frequently reported was the individualized weekly text and email reminders (*n* = 43), followed by in-app tracking (*n* = 43) and the educational module (*n* = 18).

Least favorite features: Among the most frequently reported app features that individuals disliked were the videos (*n* = 12): individuals most often requested access to the videos on the computer or away from the phone. This was followed by the need for print-based goal-setting (*n* = 11), and weekly email and text reminders (*n* = 9), and this was often due to the early delivery time of the messages. Interestingly, two individuals noted that they desired more frequent face-to-face interaction with study staff.

Desired features: Individuals in groups C and D most often reported desiring some type of in-app goal setting functionality (n = 11). As with those in groups A and B, these individuals also sought integration with external monitors or services (n = 10), and more frequent text and email reminders (n = 9).

Points-Related Feedback. Individuals with access to the points-based feedback module (i.e., groups A and C) most often reported the feature provided a sense of motivation to increase activity (n = 14), that they enjoyed the feeling of progress associated with the badges and levels (n = 7), and that it provided helpful feedback on progress (n = 2). These individuals often reported a desire to know more information about the specific point values associated with each in-app activity (n = 11), that levels and badges should come more frequently (n = 6), and that they would like some type of material reward (n = 5).

Education Feedback. When asked to comment on the videos directly, participants most often reported the videos were informative (n = 36), enjoyable (n = 16), and short and easy to watch (n = 16). However, these individuals most often reported they felt the videos contained information they felt they knew (n = 10), they desired information that was more broad and related to other health behaviors (n = 6), they felt the videos were long (n = 5), and desired reminders to watch the videos throughout the week (n = 4).

Technical and Design Issues. Two primary categories of technical issues emerged from the feedback. The first related to a user interface element (i.e., slide control) that was used to increase or decrease activity duration and frequency, and to enter intensity and enjoyment. A total of nine entries noted the sliders were overly sensitive. Additionally, an update to the Apple iOS operating system during the study period prevented saving activities when on the local university wireless internet network due to firewall issues, and this was reported in seven cases. Finally, though this was not reported within the feedback forms, one additional technical error emerged whereby the video tracking feature utilized in this study was removed by the provider (i.e., YouTube), preventing the ability to monitor video viewing behavior during the final six weeks of the study period.

Chapter 5: Discussion

The present study aimed to test the individual and combined efficacy of two theory-guided smartphone app modules (i.e., guided hierarchical goal-setting and points-based feedback) meant to improve MVPA in the context of an individualized, goal-driven physical activity intervention. Using a randomized factorial design, the efficacy of these modules was tested above and beyond a base-app containing several features commonly found in eHealth applications (Glynn, Hayes, & Casey, 2014; Hurling et al., 2007). This feature-set included a tracking module, in-app and bi-weekly individualized feedback, and an education module that included weekly SCT-based videos, quiz questions, and supportive resources. With regard to the primary aim of the study, individuals across all conditions demonstrated a mean increase in MVPA of more than 11 minutes per day. Moreover, individuals with access to points-based feedback module maintained a level of daily MVPA that was approximately 6 minutes greater than those without points-based feedback. This pattern held true across many measures collected in this study: those who received the points-based feedback module demonstrated better outcomes relative to those without the module with regard to barriers self-efficacy, exercise self-efficacy, perceived goal setting ability, several subdomains of outcome expectations, and weekly application accesses. Additionally, the presence of points produced greater effect sizes on all measures with the exception of daily MVPA and exercise-related goal setting, for which substantial time effects were present. The availability of the goal-setting module was associated with marginally higher scores for exercise-related goal setting, and a greater number of weekly application accesses.

Although these early results only partially support the primary hypothesis, they are informative and promising nonetheless. It is apparent that the base-app was fairly effective for increasing physical activity in the short term. Because this app included a set of well-studied eHealth tools, the intent was to allow for the examination of the unique impact of the two intervention modules. Unfortunately (with regard to the primary aim of the study), this package may have been sufficiently motivating so as to mask the effects of the individual intervention components. In fact, the mean level of MVPA at the end of the intervention was quite high (i.e., more than 45 minutes per day), which may have approached a ceiling effect. The results from the qualitative feedback surveys point to several aspects of the base-app that may have driven this effect. Participants emphasized the role of highly tailored bi-weekly feedback, which was tied to daily self-monitoring, for motivating increased MVPA across the 12-week study period. Again, though unexpected, there is promise in this finding, as the ability to automatically provide supportive, individualized information is one of the greatest strengths of eHealth and mHealth platforms (Fanning et al., 2012; Nahum-shani, Hekler, & Spruijt-metz, 2015). In fact, participants often reported wanting more frequent delivery of motivational messages and reminders for basic tasks (e.g., tracking activity, watching videos). These findings align well with Ritterband and colleagues' seminal Behavior Change Model for Internet Interventions (Ritterband, Thorndike, Cox, Kovatchev, & Gonder-Frederick, 2009). The researchers posited that website use should lead to behavior change through a number of mechanisms of change (e.g., improvements in self-efficacy), and they note that usage is impacted by characteristics of the user (e.g., psychophysiological factors), the environment, and the website or application (e.g., the user interface, behavioral prescriptions, ease of use), as well as by the support (e.g., email, phone calls, text-messages) provided to the individual. In the context of MAPS, individuals reported that automated messages (i.e., support) were indeed motivating, and this was reflected in relatively high use rates across the 12 week intervention. Moreover, use was higher among individuals with access to either intervention module, and it is plausible these features, when combined, contributed to the participants' positive response to the intervention. Recent meta-analytic evidence from Donkin et al. (2011) supports this relationship between website or application use and behavior, finding that higher usage rates are associated with better intervention outcomes across a number of behaviors including food and vegetable consumption, physical activity, and weight management.

Still, the base-app's self-monitoring-centered approach is not likely sufficient to promote long-term behavioral maintenance (Bravata et al., 2007; Webb et al., 2010). It was for this reason that a central focus of MAPS was the importance of high-quality, structured, and nested goals. Bandura (1997) noted that distal goals are important for guiding an individual's behavior and for organizing one's values, but proximal goals, which are progressive, challenging, and attainable, provide powerful rewards and indicants of mastery that can drive long-term behavior change and maintenance. Although individuals were unaware of features provided to participants in other experimental conditions, those assigned to a condition without in-app goal-setting most frequently reported a desire for the feature, and noted that they often forgot to use the print-based goal materials (e.g., "I began to try to set the goals in my head"). This highlights a tremendous advantage afforded by the smartphone: because the device is typically carried by the individual at all times, intervention materials remain readily accessible. When the individual receives a reminder, for example, to set and revisit their goals, all of the necessary tools are available at the swipe of a finger. Relative to individuals with print materials, who often noted they attempted to maintain weekly goals in their memory, it is likely that goal-module-equipped individuals engaged in more structured goal setting practice, which may serve to better guide behavior in the long term. The results of this study did not provide firm evidence to this effect, and this is, perhaps, unsurprising. All individuals within the study received goal-setting counseling that included concise distal goals and a clear progression for setting and revisiting weekly goals, thereby making some level of mental goal management more feasible in the short term. Additionally, though the module did provide an avenue for mastery experience by way of supportive in-app messaging when goals were met, these experiences were available much less frequently when compared to those provided by the points-based module. Clearly, additional research is needed to determine the efficacy of the goal-setting module without intensive face-to-face goal counseling, and for promoting the long-term maintenance of activity behavior.

The evidence related to the points-based feedback system was much clearer in this study. Findings suggest this module may offer one potent strategy for positively impacting MVPA, important psychosocial factors, and the degree to which an individual interacts with an mHealth application. This module was constructed as a novel approach to implementing effective feedback (Bandura, 1997). Specifically, the aim was to deliver feedback instantly, alongside completion of a desired behavior, and to weight this feedback to account for the type and difficulty of the task. In turn, it was theorized this would provide incremental indicants of an individual's mastery experiences during the adoption of a new behavior, and the results of this study provide early evidence that such an approach may indeed be effective. Despite high levels of MVPA across all individuals, those with access to this component maintained still higher levels of PA across the intervention period. Interestingly, individuals without access to the component demonstrated decreases in several domains of self-efficacy, while those with the points-based feedback module reported maintenance or improvements in these domains. These individuals also reported better outcome expectations for exercise, and a better ability to set and meet goals relative to those without the points-based system. This finding is again in line with the tenets of social cognitive theory. While higher efficacy should promote physical activity directly, it is also likely to impact one's ability to set and meet goals, their perceptions of barriers in their environment, and the degree to which they hold healthy outcome expectations. Over time, it can be expected that these improvements will contribute to more meaningful and longer lasting behavior change (Bandura, 1997, 2004).

There were several intriguing findings relative to the qualitative feedback. First, although individuals with access to the goal-setting module most often reported liking the structured goal recommendations, several also noted the goal suggestions were overly restrictive. Specifically, they noted a desire to set maintenance goals at an earlier level of physical activity (i.e., prior to achieving public health recommendations for physical activity). This highlights a unique challenge for mHealth and eHealth researchers. Whereas a key advantage of these platforms is their ability to deliver individualized programs that provide a great deal of personal agency (e.g., to influence intervention progression), this approach may not sufficiently motivate an individual to set and achieve challenging health goals. A large body of research suggests the presence and characteristics of an exercise leader (e.g., motivation, enthusiasm) may impact various program outcomes, including adherence and exercise intensity (Estabrooks et al., 2004; Loughead, Colman, & Carron, 2001). Without the presence of a live exercise leader, it is important that exercise programs delivered away from a health center develop strategies to motivate individuals to move beyond what they find comfortable. Programs targeting non-aerobic activity have been successful in delivering monthly video-based exercises featuring effective exercise leaders (McAuley et al., 2013), but such an approach would not be feasible in MAPS, which delivers an individualized exercise program that partially focuses on aerobic activities. In the present study, weekly videos were meant to convey a consistent program leader, but qualitative feedback indicated that these videos were not equally viewed by all participants. To maintain a focus on progression, one simple strategy may be to provide a motivational cue that includes a reminder of one's distal goal while the individual sets their weekly proximal goal.

A second interesting finding was in the degree of heterogeneity with regard to individual preferences for application features. For instance, whereas some individuals found weekly reminders so motivating as to ask for more frequently delivery, a minority noted they were displeasing and intrusive. Some individuals noted that the points system was highly motivating and a good indicant of progress, while others noted the rewards felt arbitrary and non-material. Fortunately, recent years have seen the development of a number of effective frameworks that are well suited to eHealth-delivery, and which can harness this heterogeneity to craft intervention materials to the individual (e.g., just-in-time adaptive interventions, JITAI, Nahum-shani et al., 2015; sequential multiple-assignment randomized trials, SMART, Collins et al., 2007). These are discussed in detail below.

Taken together, the findings of the present study serve two important roles. First they are of value to commercial and research developers creating technology-delivered PA interventions. They build on evidence pointing to the importance of sustained and highly-tailored email and text communications for promoting use of the mHealth intervention materials (Donkin et al., 2011; Murray, 2014; Ritterband, Thorndike, Cox, et al., 2009). Additionally, this study provides evidence in support of the use of a social cognitive theory-guided points-based feedback system for impacting physical activity and important social cognitive constructs. Finally, it provides early support for the usability and utility of in-app goal setting for guiding individualized activity programs and ongoing user feedback.

In addition to providing useful information to those interested in developing physical activity-promoting technologies, this study lays a strong foundation for future research. Each phase of the MOST framework, including the *preparation* phase, functions iteratively, with the express purpose of identifying and optimizing effective intervention components. A key goal of the *preparation* phase is to pilot the theory- and research-driven study design (Collins, Nahum-Shani, & Almirall, 2014), and in the present study it was apparent that the control condition was overly effective. A clear next step is to conduct a second *preparation* phase study that incorporates the user feedback from the present study into each study component (e.g., by providing more frequent reminders, providing daily tracking prompts and longitudinal feedback, revising the educational content to avoid repetition of orientation content) while implementing an alternative control condition. For example, individuals in the control condition may receive weekly automated emails containing general health-related tips and advice, an approach similar to one utilized by McAuley and colleagues (2012, 2013). Additionally, follow-up research may include measures of self-efficacy during the early stages of the intervention period. McAuley et al. (2011) noted that one's efficacy often changes dramatically following the initial weeks of a health behavior intervention. The authors posit this may reflect a recalibration of efficacy beliefs whereby individuals who are inexperienced in a specific behavior may enter the intervention with an artificially inflated sense of self-efficacy. These ratings of self-efficacy often decrease rapidly when introduced to the challenging behavior. Accordingly, while a pre-post assessment of efficacy may not show significant change (as was often observed in this study), a comparison of change in efficacy from the early weeks of an intervention to the end of the study may be more informative. Additional research incorporating measures of efficacy after the start of the intervention may also provide clarity for several interesting trends in efficacy observed in this study (e.g., the interaction effects observed between time, points, and goal setting on exercise self-efficacy). One particularly interesting area for future research in mobile physical activity intervention delivery is the incorporation of ecological momentary assessment (EMA) techniques (Shiffman, Stone, & Hufford, 2008) to collect serial assessments of efficacy beliefs over the course of the intervention. Such an approach may substantially deepen our understanding of the ways in which efficacy beliefs change in response to an intervention, and the ways in which these changes in turn impact intervention outcomes.

Upon identification of the most effective intervention components, an *optimization* phase study is warranted, in which the goal is to identify the optimum components delivered at optimum levels and in the most effective order. Importantly, Collins et al. (2007) indicate this phase is well-suited for the implementation of a time-varying adaptive intervention approach (e.g., JITAI, SMART). SMART is one adaptive framework that has received considerable attention in recent years, and it recognizes and aims to utilize the large amount of heterogeneity present in human behavior (Collins et al., 2007). Using this approach, researchers specify a sequence of decision rules that adapt the intensity or type of treatment to the individual's needs. This allows a researcher to determine the optimum levels and order of delivery for each intervention component while considering the needs of the individual. An illustration in the context of the MAPS protocol is depicted in Figure 22. Briefly, an individual may be randomized initially to receive all components (i.e., base-app + goals + points), or the base-app + goals alone. Because the primary outcome is level of physical activity, self-reported activity data might be analyzed following the third week of the program to detect whether an individual is responding positively or negatively to the intervention. At this time, a second randomization would occur such that responsive individuals from the base-app + points + goals group may be randomized to continue with the full app, or may receive a stepped-down version in which the points feature is removed. Those who are non-responsive may be randomly assigned to continue with the app as-is, or to receive an enhanced-feedback version that includes daily prompts for activity. Responders from the base-app + points group might be randomized to continue without points, or to a further-reduced version in which feedback is provided only once-weekly. Non-responders in this condition may continue without points, or may be randomized to receive the points feature. Similar randomizations would occur at key points during the intervention period based upon response since last randomization. Such an approach has a number of intriguing advantages. First, by pre-specifying an order in which features are stepped-up or stepped down, researchers may identify person-level predictors that indicate which features are needed to produce a successful intervention, or to boost the efficacy of an intervention during times when participants are most likely to begin to relapse. Additionally, the approach works toward providing extra support to individuals who most need it, while providing the leanest intervention to those in need of less, and who may, in fact, find frequent prompts intrusive.

Strengths

There are a number of important strengths in the present study. It tested the individual efficacy of two theory-based smartphone-delivered tools, and identified one that appears to be an effective driver of PA in the short term. MAPS also represents an innovative approach to PA intervention that is highly tailored and theory-driven. As the program was supported by individual goals, and because the goal-setting module utilized individual progress to generate goal recommendations, the intervention was tailored to the success and preferences of the individual. Additionally, the program automatically delivered individualized feedback in a number of forms (i.e., email, text message, the feedback module, the points module), and these appeared to provide significant motivation for activity. This automaticity, alongside the program's cross-platform compatibility and very low operating costs, highlight an approach that is readily scalable and broadly deliverable. Moreover, the program was successful in maintaining a high degree of use across conditions, such that even among those in the least active condition (i.e., group D), participants accessed the app approximately once per day by the end of the 12 week period. Finally, although the participants recruited to participate in this study did not engage in regular, structured exercise at baseline, it is apparent they engaged in a rather high level of lifestyle physical activity prior to the start of the program. MAPS was effective in promoting PA even among these individuals.

Limitations and Future Directions

Of course, there were several limitations present in this study. First, due to the constraints of this *preparation* phase study, long-term follow-up data are not available for analysis. This is particularly salient, as positive PA effects were present across conditions, but there were differential effects by condition with regard to a number of psychosocial and access variables. Accordingly, while this hints at the long-term utility of specific intervention components, additional research is warranted. Similarly, due to time constraints with regard to participant recruitment, it is possible that a seasonal effect may have influenced participant physical activity levels. It is important to note, however, that recruitment occurred in a rolling fashion, and all participants began and ended the study during the winter and early spring months when weather in central Illinois is fairly consistent. Moreover, participants were primarily well-educated white women living near a large university, so it may be important to examine the impact of the MAPS approach among other populations to determine the generalizability of these findings. Finally, many participants expressed a desire to integrate commercial activity monitors into the application to reduce the burden of manual activity entry. Due to the considerable number of devices on the market, each with a different activity-detection algorithm and ruleset allowing or disallowing capture of activity data by outside sources, accomplishing this goal would reduce the scalability of the MAPS study application, which is among its chief strengths. These devices are also best-suited to capture locomotor activity, and do not effectively capture and quantify non-aerobic activities. Similarly, although a phone's internal accelerometer allows for the capture of some activity data, and indeed the iOS and Android platforms offer frameworks for capturing these data, such an approach requires the individual to carry the phone on the person during all exercise. Instead, the tracking system utilized by groups A and B, which had simple buttons for goal-related activities (see Figure 4), appeared to be a step in the right direction, and qualitative feedback provided by participants contained several other tips for enhancing ease of entry (e.g., provide activity menus that populate with frequently-entered activities). Future work should continue to consider methods for easing participant burden in this regard and for identifying methods of reducing the desire for retrospective activity tracking.

Conclusions

This study offers promising early evidence for the short term efficacy of a points-based feedback system in addition to a theory-based, evidence-driven basic smartphone feature-set for improving PA and several important social cognitive constructs. Importantly, this information is of immediate use to commercial and research program developers who are interested in developing PA applications. Moreover, it provides a strong foundation for the development of future work that incorporates that qualitative feedback from the present study and that tests the efficacy of these intervention components against an alternative control condition. As commercial developers and members of the general public continue to turn to technology to address important health behaviors, it is vitally important that researchers work toward producing information in a timely manner that can effectively guide the evolution of these tools. In so doing, we may begin to have a meaningful impact on the health of the nation by shifting the tide away from an overabundance of ineffective, a-theoretical applications available to consumers (Yang, Maher, & Conroy, 2015), to the broad availability of effective, science-driven health applications.

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Figures

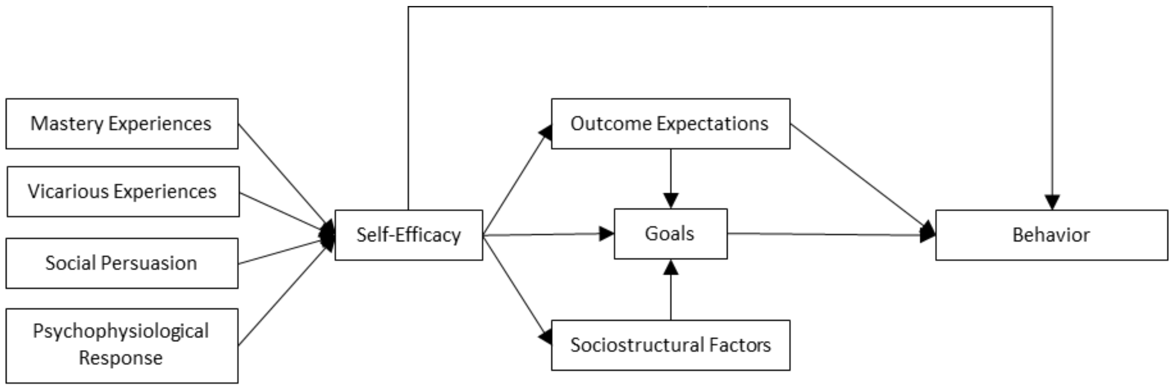


Figure 1: Structural paths of influence in the Social Cognitive Theory, adapted from Bandura, 2004.

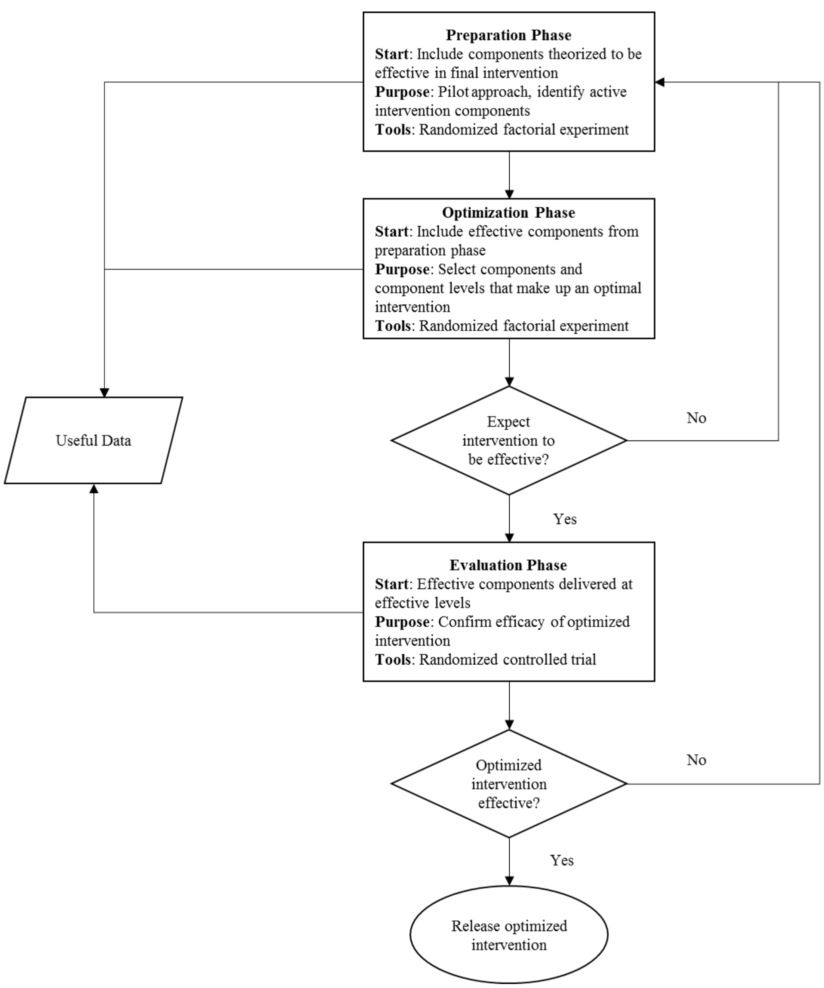


Figure 2: Outline for the Multiphase Optimization Strategy. Adapted from Collins (2014*)*

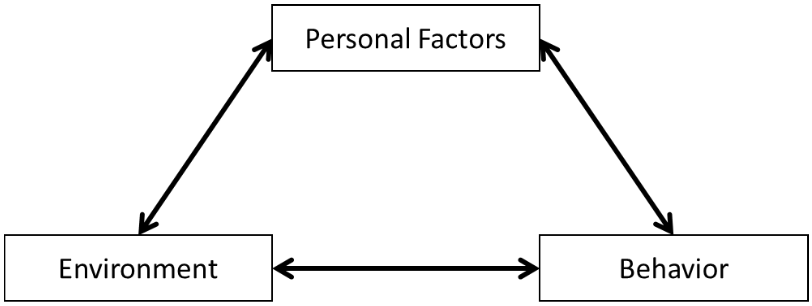


Figure 3: Triadic reciprocal determinism, adapted from Bandura (1986)

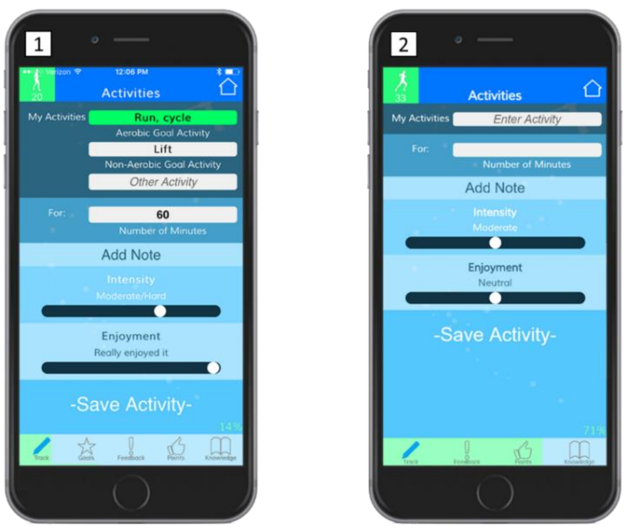


Figure 4: Screenshots for in-app tracking. Note: 1=Tracking screen for groups A & B; 2=Tracking screen for groups C &D

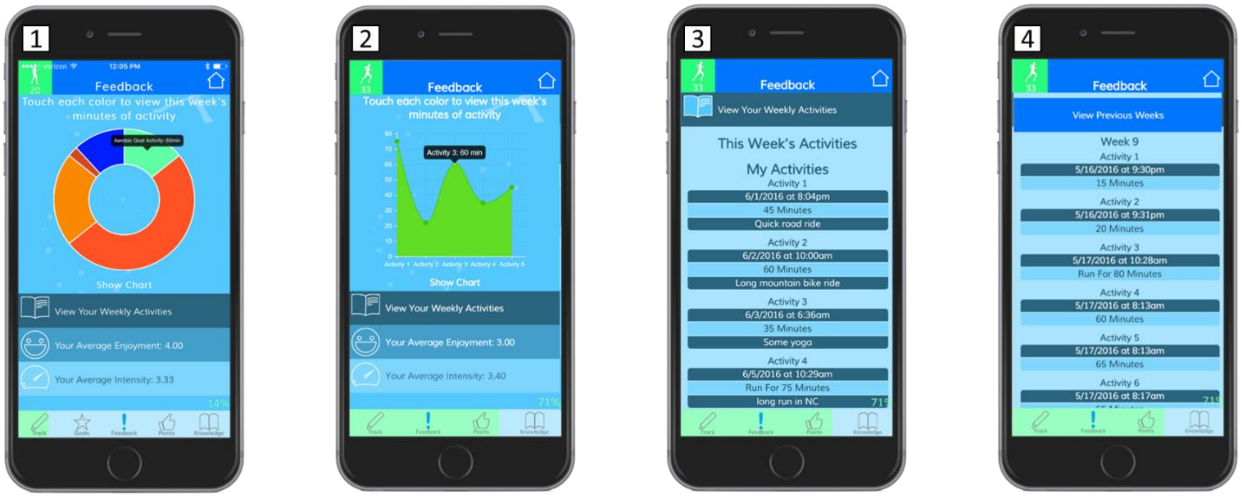


Figure 5: Screen shots for in-app feedback. Note: 1=Example feedback screen for groups A & B; 2=Example feedback screen for groups C & D; 3=Example weekly diary; 4=Example history diary.

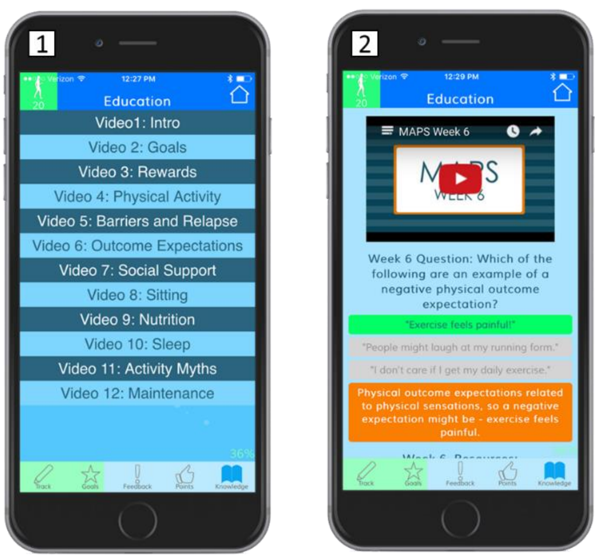


Figure 6: Screenshots for the knowledge feature. Note: 1=Screenshot showing all education modules during the 12th week of the program; 2=Screenshot depicting the outcome expectations video and answered quiz question.

Good morning

Welcome to **week 2** of the MAPS study! As with each week of the study, you have a new video available to you, so be sure to head to the **knowledge** area to give it a watch. It's all about goals, and you will be able to use this information right away, as you also have your first opportunity to review your **goals**! It looks like you met at least one of your goals last week, so head straight to the *goals page* to review last week's goals and set new ones. Remember that MAPS will make goal suggestions for you, so use those to consider how you want your next week to go. And remember that if you want to stick with this, it's important that you slowly build your goals each week! For these first four weeks, think about increasing the amount of time you are spending exercising before you increase the number of days of exercise.

Below you will find some information from your first week in the program.

Last Week's Aerobic Goal:	To **Walking, videos** on **3** days for **15** minutes at a time for a total of **45** minutes. You exercised on **4** days for a total of **60** minutes. Way to meet your **total goal minutes**!
Last Week's Non-Aerobic Goal:	To **Weights, yoga** on **1** days for **15** minutes at a time for a total of **15** minutes. You exercised on **1** day for a total of **15** minutes. Way to meet your **total goal minutes**!
	You did not do any other activities this week.
Your Average Enjoyment was:	4.25 (Somewhat enjoyed it)
Your Average Intensity was:	4.25 (Moderate/Hard)

As always, let us know if you have any questions,

The MAPS Team

Figure 7: Example automated feedback email.

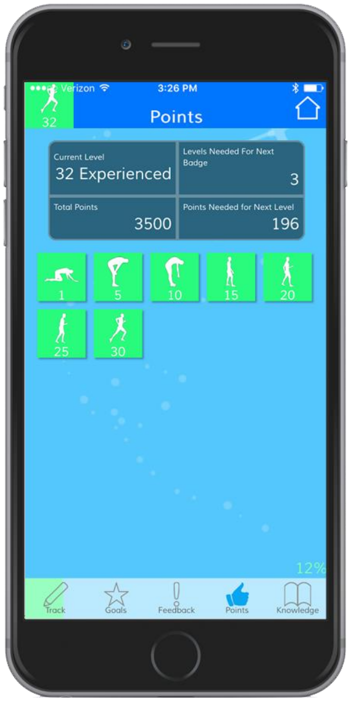


Figure 8: Example "Points" screen with badges

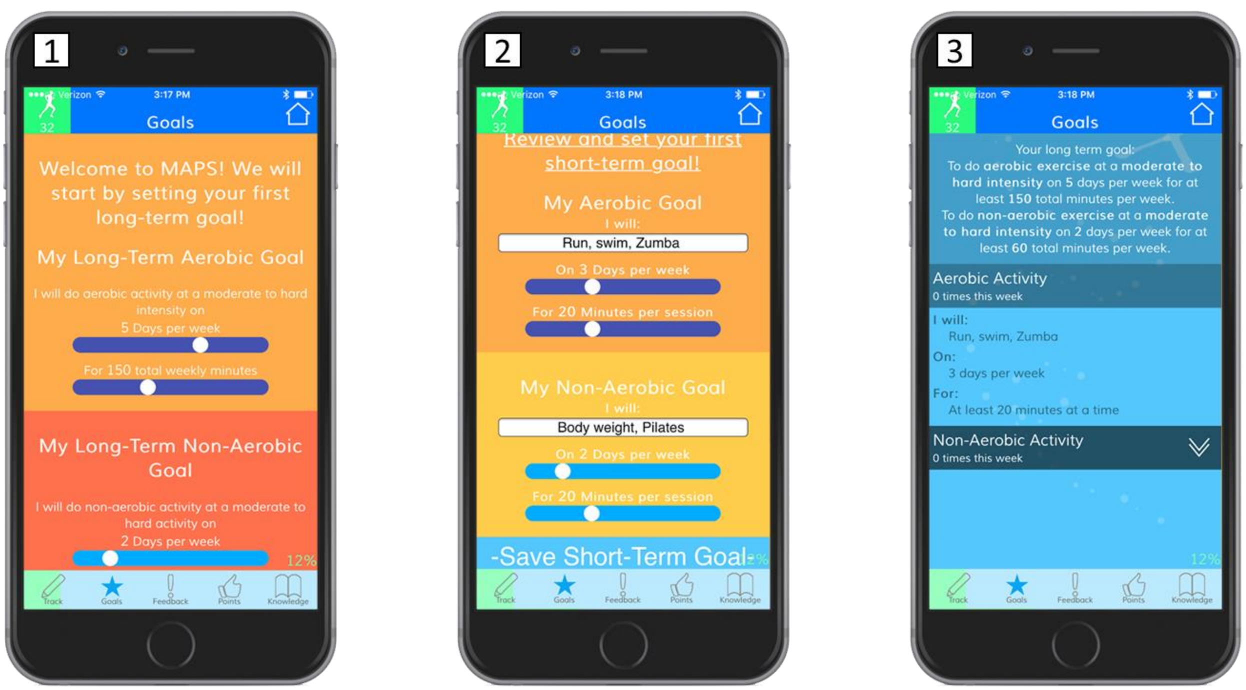


Figure 9: Example goal-setting screens for those in groups A or B. Note: 1=Example distal goal screen; 2=Example short term goal screen; 3=Example goal monitoring screen.

Figure 10: Example short-term goal worksheet from the goal-setting handbook used by groups C & D

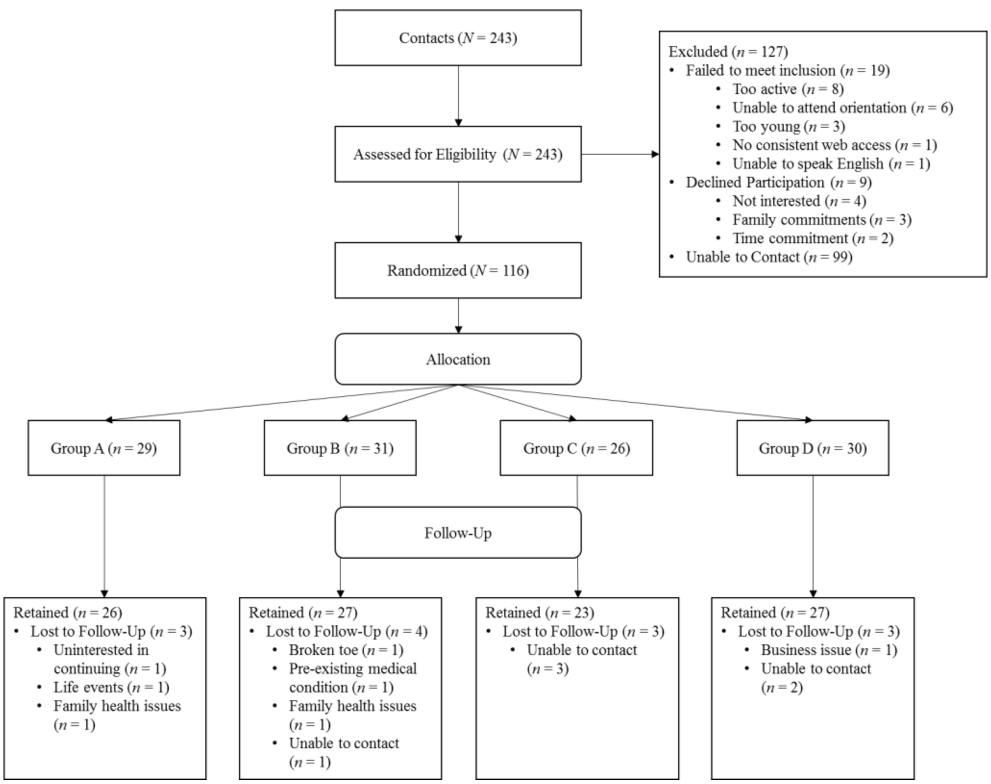


Figure 11: Study CONSORT diagram.

Figure 12: Mean change in daily minutes of MVPA (adjusted for education) from baseline to week 12. The left graph compares those with and without the points module, the right graph compares those with and without the goal-setting module.

Figure 13: Mean change in barriers self-efficacy from baseline to week 12. The left graph compares those with and without the points module, the right graph compares those with and without the goal-setting module.

Figure 14: Mean change in exercise self-efficacy (adjusted for gender) from baseline to week 12. The left graph compares those with and without the points module, the right graph compares those with and without the goal-setting module.

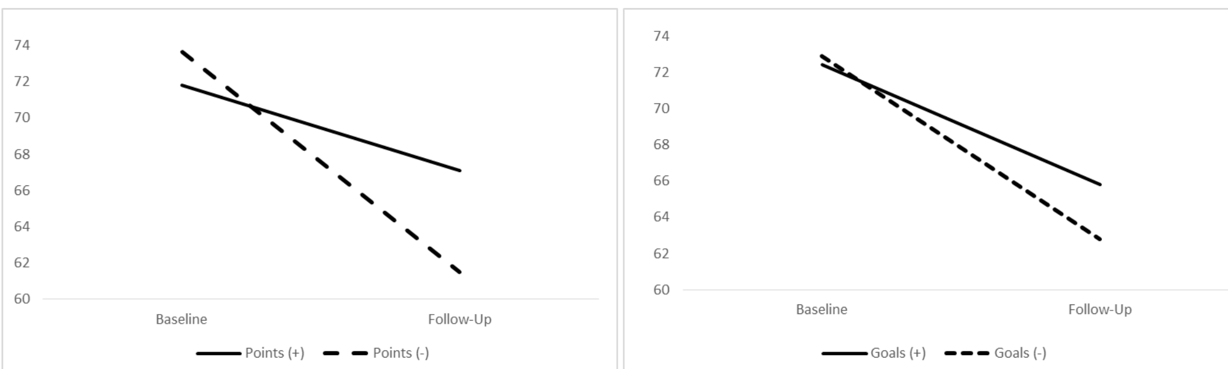


Figure 15: Mean change in lifestyle self-efficacy from baseline to week 12. The left graph compares those with and without the points module, the right graph compares those with and without the goal-setting module.

Figure 16: Mean change in exercise goal setting (adjusted for race) from baseline to week 12. The left graph compares those with and without the points module, the right graph compares those with and without the goal-setting module.

Figure 17: Mean change in physical outcome expectations for exercise from baseline to week 12. The left graph compares those with and without the points module, the right graph compares those with and without the goal-setting module.

Figure 18: Mean change in self-evaluative outcome expectations for exercise from baseline to week 12. The left graph compares those with and without the points module, the right graph compares those with and without the goal-setting module.

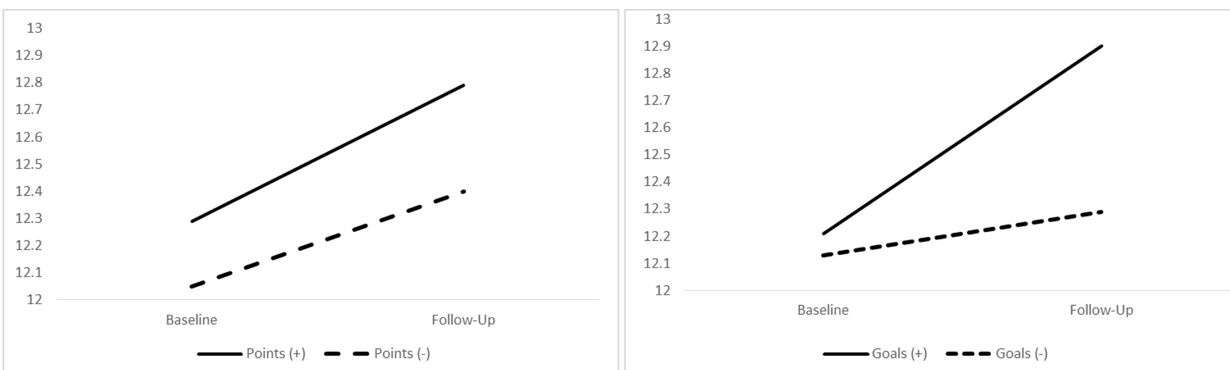


Figure 19: Mean change in social outcome expectations for exercise (adjusted for gender and income) from baseline to week 12. The left graph compares those with and without the points module, the right graph compares those with and without the goal-setting module.

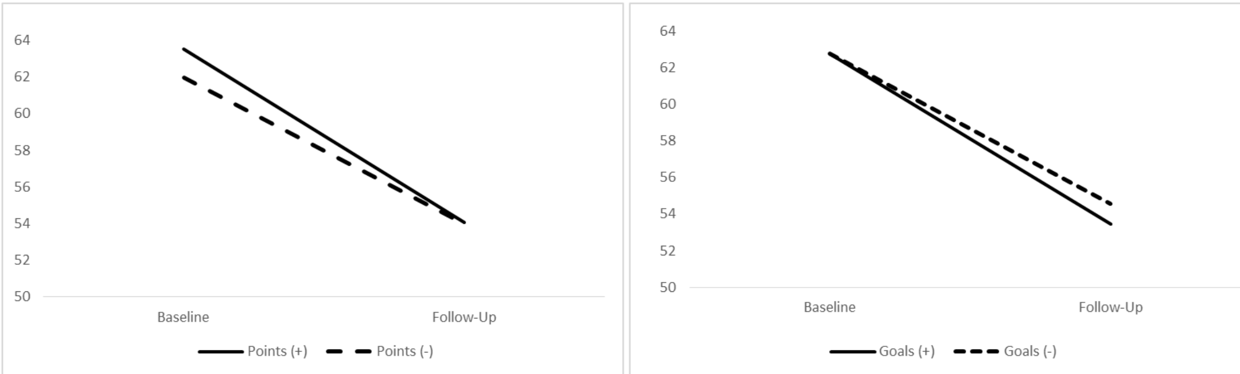


Figure 20: Mean change in perceived barriers to exercise (adjusted for gender) from baseline to week 12. The left graph compares those with and without the points module, the right graph compares those with and without the goal-setting module.

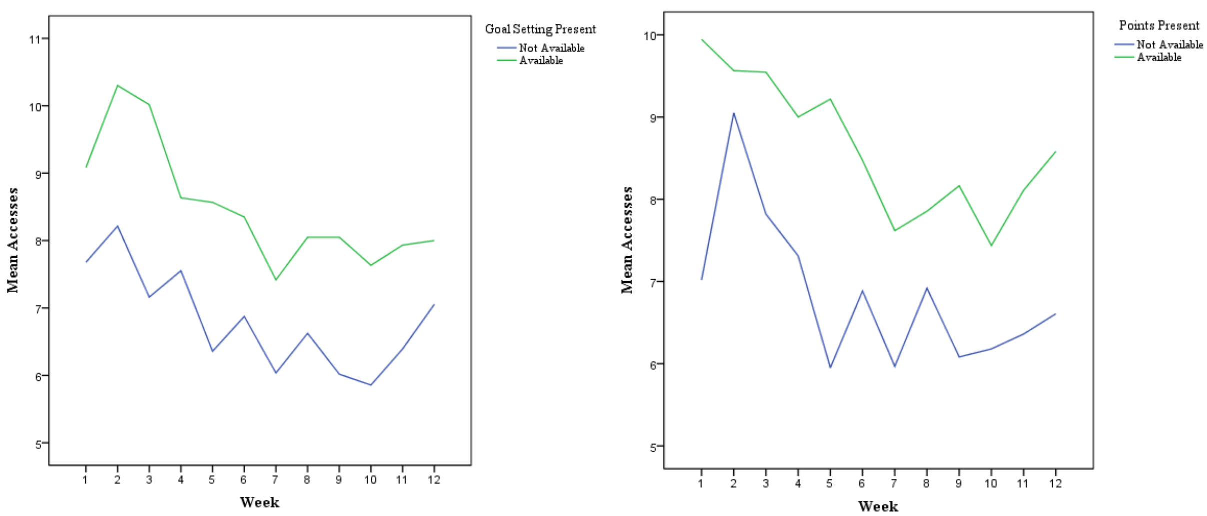


Figure 21. Application accesses across the 12 week program. Note: The graph on the left depicts accesses per week for those with and without access to in-app goal setting; the graph on the right depicts accesses per week for those with and without access to points-based feedback.

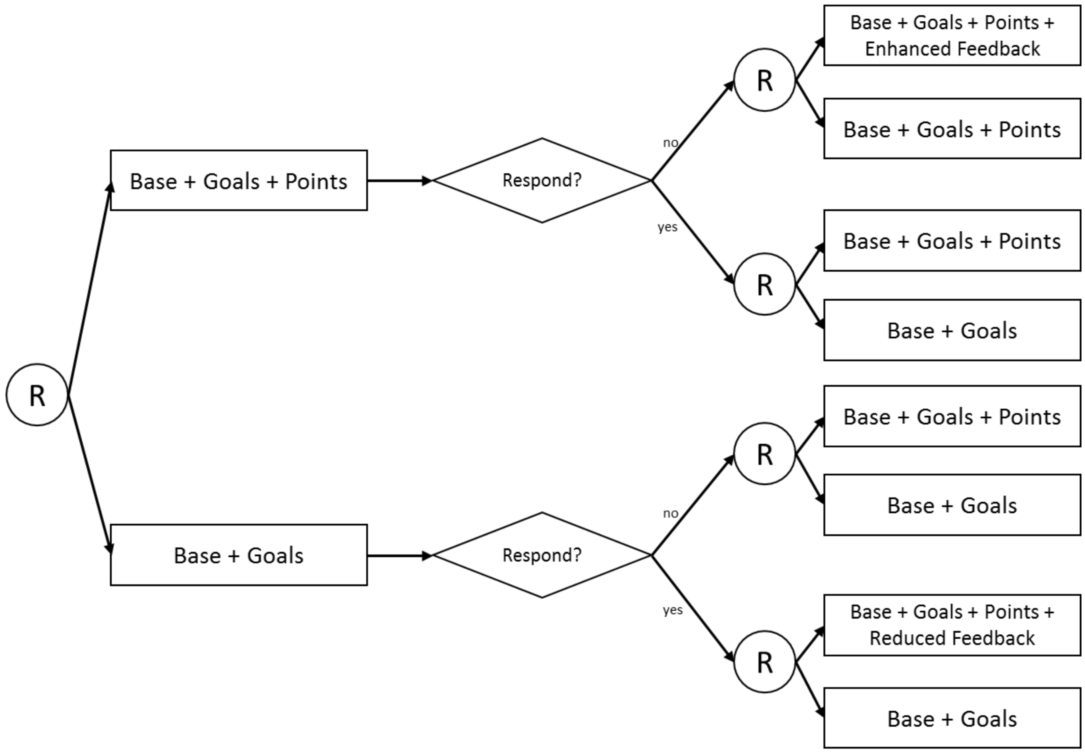


Figure 22: Example sequential multiple-assignment randomized trial (SMART) approach to the present study.

Activity Level	Moderate Intensity Minutes per Week	Benefits	Notes
Inactive	None above baseline activity	None	Being inactive is unhealthy
Low	Some activity above baseline, but less than 150 minutes per week	Some	Low levels of activity are preferable to an inactive lifestyle.
Medium	150 - 300 minutes per week	Substantial	Activity at the high end of this range has additional benefits above those obtained at the low end.
High	Greater than 300 minutes per week	Additional	Currently, science has not identified an upper boundary for activity beyond which there are no additional benefits.

Table 1: Classification of total weekly amounts of aerobic physical activity into four categories. Adapted from HHS (2008).

Group	Goal Setting Module	Point-based Feedback Module
A (*n*=29)	+	+
B (*n*=31)	+	-
C (*n*=26)	-	+
D (*n*=30)	-	-

Table 2: Group allocation and activated app features. Note: (+) = activated; (-) = deactivated

Action	Group	Program Points (*pp*)
Log Aerobic Activity (limit 3/day)	A, B	10
Log Non-Aerobic Activity (limit 3/day)	A, B	10
Log “Other Activity” (limit 3/day)	A, B	5
Log Activity (first two)	C, D	10
Log Activity (additional)	C, D	5
View Weekly Educational Video (first time)	A, B, C, D	10
Answer Weekly Quiz Question (once)	A, B, C, D	5
Achieve Short Term Goal	A	$\text{constant} + \left(\text{constant} * \left(n_{\text{goals met}} - 1\right)\right)$ where constant = 5
Achieve Long Term Goal	A	$\text{constant} + \left(\text{constant} * \left(n_{\text{goals met}} - 1\right)\right)$ where constant = 10

Table 3: Allocation of program points (pp)

Level	Points	Title	Badge	Motivational Text
1	0	Rookie		You've decided to join the MAPS program, which is a big step in the right direction! Now that you're on the road to an active lifestyle as a Rookie Exerciser, it's important that your first steps are gradual ones. Set your goals so that they are challenging but achievable!
5	100	Rookie		Way to go – you have already demonstrated a commitment to an active lifestyle! You are half-way to your new title, so keep it up! As you push forward, remember that you will need to make a commitment to open the MAPS app each day to track your activities, check in with new Knowledge content, and view your weekly progress.
10	450	Apprentice		"Alright, you're officially an Apprentice Exerciser! This means that you have clearly committed to being active – great job! At this point you have probably began to encounter barriers to your active lifestyle, and perhaps you have had a few setbacks. Congratulations on pushing through those! One thing that defines those that stick with activity is their ability to bounce back from setbacks. Keep revisiting your goals, and keep approaching each week with a fresh outlook."
15	1050	Apprentice		"Another day another badge! Until your next Title, your task is to revisit the goal activities that you are doing each week. You have selected some good ones if you find that you often look forward to doing your activities. If you find that you often dread doing one or more, however, then try to think up some new activities to try out. You won't always feel like exercising, but you should find things that you get enjoyment from."
20	1900	Full		"Wow, you did it – You are a Full Exerciser! You should feel very proud of the effort that you have clearly put in to get to this point. You should feel like you are getting a good grasp of what is needed to set goals and stay active. From this point forward, make a focused effort to keep things fresh. Each week, make sure you spend a few more seconds to think of goals that will be fun and challenging. Try to explore new activities that you have not yet done, or select an event such as a 5k, obstacle course, or charity walk to work toward."
25	3000	Full		"Great! You have earned a new badge and you are half way to your next Title! During your third week in the MAPS program you received a video about Rewards. Given how far you have come, it might be worth giving that another watch. Then, start to think up a reward to give yourself for reaching your next Title and Badge!"

Table 4: Points lookup table

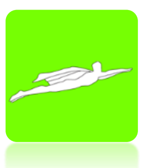
Level	Points	Title	Badge	Motivational Text
30	4350	Experienced		"You are now an Experienced Exerciser! If you have been sticking to your goals and revisiting them each week, you are likely ready to share your wealth of knowledge and experience! If you haven't already, try to find an exercise partner to team up with. This will help each of you set and achieve your goals each week."
35	5950	Experienced		"You are half way to your next Title! MAPS tends to focus on one type of physical activity: Leisure-time physical activity. We have talked about the other types of physical activity, including lifestyle and transport activity. As you work toward your next Title, try to think of some ways to add these types of activity into your daily life. For example, walking to the store instead of driving will leave you refreshed and in a better mood."
40	7800	Expert		"You're an Expert Exerciser! At this point, you probably feel like you know what it takes to stay active, and you know how to stick with it even when times are tough. This is exactly how you should feel, so give yourself a big pat on the back!"
45	9900	Expert		"Here's another badge for you! You're well on to your way to the big level 50 – as you work in this direction, start to think about applying the skills that you have learned in MAPS to other behaviors. For example, did you know that sleeping is one of the most important things you can do to live a long and health life? Did you know that it is important to avoid sitting for extended periods of time – standing briefly every so often is enough to avoid negative health issues. Think about setting some easy goals relative to these other behaviors!"
50	12250	Lifelong		"Holy cow – you made it all the way to level 50! At this point you are a lifelong exerciser. You have all the skills that you need to live an active lifestyle, and you are ready to serve as a model for others! This is the last Title and Badge that we have for you, but you can keep moving forward with setting goals and tracking your behavior. We are proud of you!"

Table 4 (cont.): Points lookup table.

Goal Type	Frequency (Min - Max, Recommended; day) *Conditions*	Duration (Min - Max, Recommended; min) *Conditions*
Initial	Aerobic: 1 - 7, 3 Non-Aerobic: 1-7, 2	1-60, 15 1-60, 15
No Success	PF $\pm$1day, PF *1 ≤ Minimum ≤ 5* *Minimum ≤ Recommended ≤ 5* *3 ≤ Maximum ≤ 7*	(PD-15%) – (PD+15%), PD *10 ≤ Minimum* *Maximum ≥ 10 or PD + 5*
Success First 4 Weeks	LM, LM+1, LM *1 ≤ Minimum ≤5* *2 ≤ Maximum ≤ 7* *Recommended ≤ 5*	LM+15%, LM+50%, LM+35% *Set maximum to median duration of successfully met goals, unless that is less than LM+50%*
Success Last 8 Weeks	LM, LM+2, LM+1 *1 ≤ Minimum ≤5* *2 ≤ Maximum ≤ 7* *Recommended ≤ 5*	LM+15%, LM+35%, LM+25% *Set maximum to median duration of successfully met goals, unless that is less than LM+35%*

Table 5: Goal setting ruleset. Note: PF = previous goal frequency; PD = previous goal duration; LM = last met goal.

Variable	Mean (SD)/Frequency (%)
Age	41.38 (7.57)
Gender	
Female	93 (80)
Male	23 (20)
Married	89 (77)
White	101 (87)
College Graduate	98 (84)
Earning ≥$75,000/year	60 (52)

Table 6: Participant demographics at baseline

Effect	F	η^2	P
Time	74.860	.42	<.01
Points	4.011	.04	.05
Goals	.005	.00	.94
Time x Points	.145	.00	.70
Time x Goals	.164	.00	.69
Points x Goals	.814	.01	.67
Time x Points x Goals	.615	.01	.44

Table 7: Intervention effects on accelerometer-measured physical activity, adjusted for education level.

Measure	Baseline	Follow-Up	d	Grand Mean
MVPA (minutes)	34.88 (1.62)	46.77 (1.65)	0.70	40.83 (1.48)
Points (+)	38.11 (2.35)	49.48 (2.40)	0.67	37.86 (2.04)
Points (-)	31.65 (2.22)	44.07 (2.27)	0.73	43.80 (2.16)
Goals (+)	35.05 (2.29)	46.39 (2.33)	0.67	40.72 (2.10)
Goals (-)	34.71 (2.29)	47.16 (2.34)	0.73	40.94 (2.10)
Goals (+) x Points (+)	39.08 (3.29)	50.98 (3.36)	0.70	45.03 (3.02)
Goals (+) x Points (-)	31.02 (3.17)	41.80 (3.24)	0.64	36.41 (2.91)
Goals (-) x Points (+)	37.14 (3.36)	47.99 (3.43)	0.64	42.57 (3.08)
Goals (-) x Points (-)	32.27 (3.12)	46.33 (3.18)	0.83	39.30 (2.86)

Table 8: Means (SE) for accelerometer-measured physical activity, adjusted for education level.

Effect	F	η^2	P
Time	1.993	.02	.16
Points	.247	.00	.62
Goals	.863	.01	.36
Time x Points	10.065	.08	<.01
Time x Goals	1.041	.01	.31
Points x Goals	.086	.00	.77
Time x Points x Goals	1.667	.02	.20

Table 9: Intervention effects on barriers self-efficacy

Measure	Baseline	Follow-Up	d	Grand Mean
BARSE	48.66 (1.95)	46.00 (2.01)	-0.13	47.33 (1.74)
Points (+)	46.53 (2.86)	49.85 (2.95)	0.16	48.19 (2.55)
Points (-)	50.79 (2.64)	42.14 (2.73)	-0.41	46.47 (2.36)
Goals (+)	51.24 (2.72)	46.65 (2.80)	-0.22	48.94 (2.42)
Goals (-)	46.08 (2.79)	45.35 (2.87)	-0.03	45.72 (2.49)
Goals (+) x Points (+)	47.38 (4.00)	51.21 (4.13)	0.18	49.30 (3.57)
Goals (+) x Points (-)	55.10 (3.68)	42.08 (3.79)	-0.62	48.59 (3.28)
Goals (-) x Points (+)	45.68 (4.08)	48.49 (4.21)	0.13	47.09 (3.64)
Goals (-) x Points (-)	46.49 (3.80)	42.20 (3.92)	-0.20	44.34 (3.39)

Table 10: Means (SE) for barriers self-efficacy

Effect	F	η^2	P
Time	5.269	.05	.02
Points	.916	.01	.34
Goals	.480	.0	.49
Time x Points	.230	.00	.63
Time x Goals	.384	.00	.54
Points x Goals	.019	.00	.89
Time x Points x Goals	4.25	.04	.04

Table 11: Intervention effects on exercise self-efficacy, adjusted for gender

Measure	Baseline	Follow-Up	d	Grand Mean
EXSE	61.71 (2.29)	56.63 (2.61)	-0.19	59.17 (2.04)
Points (+)	63.02 (3.36)	59.25 (3.82)	-0.14	61.13 (2.99)
Points (-)	60.41 (3.13)	54.01 (3.57)	-0.24	57.21 (2.79)
Goals (+)	63.97 (3.19)	57.20 (3.63)	-0.26	60.59 (2.84)
Goals (-)	59.45 (3.30)	56.06 (3.76)	-0.13	57.75 (2.94)
Goals (+) x Points (+)	62.18 (4.66)	62.35 (5.31)	0.01	62.27 (4.15)
Goals (+) x Points (-)	65.77 (4.35)	52.05 (4.96)	-0.52	58.91 (3.88)
Goals (-) x Points (+)	63.85 (4.83)	56.15 (5.50)	-0.29	60.00 (4.30)
Goals (-) x Points (-)	55.05 (4.50)	55.98 (5.12)	0.04	55.51 (4.01)

Table 12: Means (SE) for exercise self-efficacy, adjusted for gender.

Effect	F	η^2	P
Time	11.86	.10	<.01
Points	.229	.00	.63
Goals	.110	.00	.74
Time x Points	2.38	.02	.13
Time x Goals	.513	.01	.48
Points x Goals	.001	.00	.97
Time x Points x Goals	.007	.00	.93

Table 13: Intervention effects on lifestyle self-efficacy

Measure	Baseline	Follow-Up	d	Grand Mean
LSE	72.67 (1.97)	64.31 (2.52)	-0.34	68.49 (1.90)
Points (+)	71.81 (2.87)	67.09 (3.68)	-0.19	69.40 (2.78)
Points (-)	73.64 (2.68)	61.52 (3.44)	-0.50	67.58 (2.60)
Goals (+)	72.43 (2.73)	65.81 (3.50)	-0.27	69.12 (2.65)
Goals (-)	72.91 (2.83)	62.81 (3.62)	-0.42	67.86 (2.74)
Goals (+) x Points (+)	71.43 (3.99)	68.76 (5.11)	-0.11	70.09 (3.86)
Goals (+) x Points (-)	73.44 (3.73)	62.86 (4.78)	-0.44	68.15 (3.62)
Goals (-) x Points (+)	71.99 (4.14)	65.43 (5.30)	-0.27	68.71 (4.01)
Goals (-) x Points (-)	73.83 (3.85)	60.18 (4.94)	-0.56	67.01 (3.73)

Table 14: Means (SE) for lifestyle self-efficacy

Effect	F	η^2	P
Time	41.285	.27	<.01
Points	7.332	.06	.01
Goals	.020	.00	.89
Time x Points	.534	.01	.47
Time x Goals	3.313	03	.07
Points x Goals	2.878	.03	.09
Time x Points x Goals	.001	.00	.98

Table 15: Intervention effects on exercise goal setting, adjusted for race

Measure	Baseline	Follow-Up	*d*	Grand Mean
Goals	19.61 (.66)	26.08 (.83)	0.80	22.84 (.64)
Points (+)	21.08 (.96)	28.12 (1.21)	0.88	24.60 (.94)
Points (-)	18.14 (.90)	24.04 (1.14)	0.74	21.09 (.88)
Goals (+)	19.00 (.92)	26.87 (1.16)	0.98	22.94 (.89)
Goals (-)	20.22 (.94)	25.28 (1.19)	0.63	22.75 (.92)
Goals (+) x Points (+)	21.55 (1.33)	30.01 (1.67)	1.06	25.78 (1.29)
Goals (+) x Points (-)	16.45 (1.27)	23.74 (1.60)	0.91	20.10 (1.24)
Goals (-) x Points (+)	20.61 (1.39)	26.23 (1.75)	0.70	23.42 (1.36)
Goals (-) x Points (-)	19.83 (1.28)	24.34 (1.62)	0.01	22.08 (1.25)

Table 16: Means (SE) for exercise goal setting, adjusted for race

Effect	F	η^2	P
Time	.052	.00	.82
Points	.752	.01	.39
Goals	1.014	.01	.32
Time x Points	3.881	.03	.05
Time x Goals	.020	.00	.89
Points x Goals	1.036	.01	.31
Time x Points x Goals	.686	.01	.41

Table 17: Intervention effects on physical outcome expectations subscale

Measure	Baseline	Follow-Up	*d*	Grand Mean
Physical OE	26.97 (.29)	27.04 (.25)	0.02	21.00 (.22)
Points (+)	26.47 (.43)	27.15 (.36)	0.23	26.81 (.32)
Points (-)	27.47 (.40)	26.92 (.34)	-0.19	27.19 (.30)
Goals (+)	27.21 (.41)	27.24 (.34)	0.01	27.22 (.31)
Goals (-)	26.72 (.42)	26.84 (.35)	0.04	26.78 (.32)
Goals (+) x Points (+)	26.36 (.59)	27.26 (.50)	0.31	26.81 (.45)
Goals (+) x Points (-)	28.06 (.56)	27.22 (.47)	-0.29	27.64 (.42)
Goals (-) x Points (+)	26.58 (.62)	27.05 (.52)	0.16	26.81 (.47)
Goals (-) x Points (-)	26.87 (.57)	26.63 (.48)	-0.08	26.75 (.43)

Table 18: Means (SE) for the physical outcome expectations subscale. Note: OE=Outcome Expectations

Effect	F	η^2	P
Time	.317	.00	.57
Points	1.098	.01	.30
Goals	.355	.00	.55
Time x Points	3.166	.03	.08
Time x Goals	.119	.00	.73
Points x Goals	.012	.00	.91
Time x Points x Goals	1.283	.01	.26

Table 19: Intervention effects on self-evaluative outcome expectations subscale

Measure	Baseline	Follow-Up	*d*	Grand Mean
Self-Evaluative OE	22.01 (.26)	22.17 (.24)	0.06	22.09 (.21)
Points (+)	21.55 (.39)	22.18 (.36)	0.23	21.87 (.31)
Points (-)	22.48 (.36)	22.15 (.33)	-0.12	22.31 (.29)
Goals (+)	22.09 (.36)	22.34 (.33)	0.09	22.22 (.29)
Goals (-)	21.93 (.38)	21.99 (.35)	0.02	21.96 (.31)
Goals (+) x Points (+)	21.50 (.53)	22.53 (.49)	0.38	22.02 (.43)
Goals (+) x Points (-)	22.69 (.50)	22.15 (.46)	-0.20	22.42 (.40)
Goals (-) x Points (+)	21.60 (.56)	21.83 (.52)	0.09	21.72 (.45)
Goals (-) x Points (-)	22.27 (.51)	22.15 (.47)	-0.04	22.21 (.42)

Table 20: Means (SE) for the self-evaluative outcome expectations subscale. Note: OE=Outcome Expectations

Effect	F	η^2	P
Time	3.043	.03	.08
Points	.347	.00	.56
Goals	.396	.00	.53
Time x Points	.054	.00	.82
Time x Goals	.672	.01	.41
Points x Goals	.195	.00	.66
Time x Points x Goals	1.536	.01	.22

Table 21: Intervention effects on the social outcome expectations subscale, adjusted for gender and income

Measure	Baseline	Follow-Up	*d*	Grand Mean
Social OE	12.17 (.28)	12.60 (.34)	0.13	12.38 (.27)
Points (+)	12.29 (.40)	12.79 (.50)	0.15	12.54 (.39)
Points (-)	12.05 (.37)	12.40 (.47)	0.11	12.22 (.36)
Goals (+)	12.21 (.39)	12.90 (.48)	0.20	12.56 (.37)
Goals (-)	12.13 (.40)	12.29 (.50)	0.05	12.21 (.39)
Goals (+) x Points (+)	12.65 (.56)	13.02 (.69)	0.11	12.83 (.54)
Goals (+) x Points (-)	11.77 (.53)	12.78 (.66)	0.30	12.28 (.52)
Goals (-) x Points (+)	11.93 (.59)	12.56 (.73)	0.19	12.25 (.57)
Goals (-) x Points (-)	12.33 (.55)	12.02 (.68)	-0.09	12.17 (.54)

Table 22: Means (SE) for the social outcome expectations subscale, adjusted for gender and income. Note: OE=Outcome Expectations

Effect	F	η^2	P
Time	36.99	.25	<.01
Points	.246	.00	.62
Goals	.115	.00	.74
Time x Points	.511	.01	.48
Time x Goals	.259	.00	.61
Points x Goals	.680	.01	.41
Time x Points x Goals	.106	.00	.75

Table 23: Intervention effects on perceived barriers to exercise, adjusted for gender

Measure	Baseline	Follow-Up	d	Grand Mean
Barriers	62.75 (0.84)	54.01 (1.07)	0.84	58.38 (.80)
Points (+)	63.53 (1.23)	54.04 (1.56)	0.92	58.78 (1.18)
Points (-)	61.97 (1.15)	53.99 (1.46)	0.77	57.98 (1.10)
Goals (+)	62.74 (1.17)	53.47 (1.48)	0.90	58.11 (1.12)
Goals (-)	62.76 (1.21)	54.55 (1.54)	0.79	58.65 (1.16)
Goals (+) x Points (+)	62.69 (1.71)	53.00 (2.17)	0.94	57.84 (1.64)
Goals (+) x Points (-)	62.80 (1.59)	53.94 (2.03)	0.86	58.37 (1.53)
Goals (-) x Points (+)	64.37 (1.77)	55.07 (2.25)	0.90	59.72 (1.69)
Goals (-) x Points (-)	61.15 (1.65)	54.03 (2.10)	0.69	57.59 (1.58)

Table 24: Means (SE) for perceived barriers to exercise, adjusted for gender.

Effect	B	SE	df	t	P
Intercept	6.904	.78	119.41	8.89	<.01
Time	-.168	.06	127.04	-2.76	.01
Points	1.875	.90	115.45	2.08	.04
Goals	1.909	.90	115.45	2.12	.04

Table 25: Hierarchical linear regression model for weekly application accesses across the twelve-week intervention. Note: B=Unstandardized regression coefficient; SE=standard error; df=degrees of freedom.