Since 1980, the prevalence of obesity among U.S. adults has more than doubled, accompanied by increases in chronic conditions like heart disease and diabetes. This high prevalence and associated disease burden continues to be a threat to public health. Despite years of efforts to stem the tide of obesity, successful weight loss has proven difficult to achieve and sustain. Motivational influences behind successful weight loss are not well-understood but are believed to include factors related to social support, exercise regulation, and self-monitoring activities. Web-based approaches using interactive technology and online social networking as strategies for motivating behavior change are increasingly being used and may provide the basis for improvements in short and long term weight loss. This exploratory study examined factors associated with weight loss and health improvement in overweight adult healthcare workers who used
interactive technology and online social networking (OSN) in a 6-month weight loss intervention. Participants used tracking instruments (a wireless physical activity tracker and scale) and an interactive website and online social network to monitor progress and communicate with other participants throughout the study period. Data from 168 technology-enabled participants that finished the 6-month intervention was analyzed with weight loss (% BMI change) as the primary outcome of interest. Changes in weight and cardiovascular and metabolic disease markers was assessed in the technology-enabled participants at 6 months and in a subsample of these participants (n=48) one year post-intervention to examine the predictive value of demographic variables (age, gender), use of technology features (OSN, activity uploaded, weight uploads), self-reported health status, weighing frequency and physical activity habits, and perceptions of benefit from study participation on short and longer term weight loss. Single and multiple variable linear regressions indicated statistically significant greater weight loss in participants who used technology features more than those that with lower utilization during the 6-month study period. Specifically, greater utilization of physical activity and weight tracking was associated with greater weight loss, for males and females. Overall utilization of the online social network was low, but greater utilization was significantly associated with greater weight loss in males (p<0.0001). To examine longer term outcomes, t-tests were used to compare weight loss from baseline to one year post-intervention in the subsample of the 6-month technology-enabled participants. From baseline to 6-months, a mean BMI change of -3.2% was observed in the subsample (p<0.001). At one year post-intervention, weight maintenance was demonstrated, with a BMI decrease of 4.7% as
measured from baseline to one year post-intervention \((p<0.001)\). Age and gender were not predictive of weight loss maintenance one year post-intervention. Correlation analyses significantly associated perceived health status and current physical activity habits with weight loss maintenance one year post-intervention. Perceptions regarding benefit from study participation were not associated with longer term weight loss. In addition, diabetes risk reduction was demonstrated in the subsample at one year post-intervention as indicated by a mean decrease in HbA1c of .10 \((p<0.05)\) and a statistically significant proportional change \((10\%)\) in fasting blood glucose for the subsample \((p<0.05)\). This preliminary examination of a multi-component approach to weight loss is suggestive of modest but favorable short and longer term weight loss and health improvement outcomes in overweight participants who used weight and activity tracking features as part of an interactive technology weight loss intervention.
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Using Interactive Technology to Improve Health: Is Weight Loss Just a Mouse-Click Away?

by

Sarah K. Grall

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

________________________________________________________________________
Sarah K. Grall, Author
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This effort would not have been possible without the love and support of my family and friends. It’s as simple as that. My parents--Dick and Barb--are responsible for my very presence. They are also the reason I remain a curious (and busy) inhabitant of this earth. I am forever grateful for the space they gave me to find my way.

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Last (but not least!) I’d like to thank my committee members for their support, expertise and patience throughout this journey.
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Using Interactive Technology to Improve Health: Is Weight Loss Just a Mouse-Click Away?

Chapter 1

Introduction

Background

In the spring of 2012 the Boston Public Health Commission launched a major weight loss challenge, spearheaded by the city’s mayor. The goal of this ambitious initiative was for the city to lose one million pounds over the next 12 months. Encouraged by a media blitz, residents were able to register for the challenge and use a specially designed website where individuals could set a weight goal, track progress and find resources to support exercise activities. A few months shy of the end of the campaign, Bostonians had logged less than 75,000 pounds lost—less than 10% of the ultimate goal. As bloggers and journalists noted, the city had a slim chance of success (Levitz & McKay, 2013). From the start, the effort was destined to fail, repeating the experience of countless other campaigns across the nation that set ambitious weight loss goals without fully appreciating the difficult task at hand. The vast majority are unsuccessful. Considering the prevalence of overweight people in the United States and the associated health and economic burdens, effective weight loss interventions are desperately needed. Yet the recent and very public Boston experience underscores two important points—changing health behaviors is difficult, and different strategies are
needed if public health efforts are to be effective and sustainable. You cannot simply use new tools in old ways and expect different results.

Excess weight is a relatively new phenomenon in the United States, with a dramatic increase in prevalence in the last three decades. Currently, two-thirds of U.S. adults and one-third of U.S. adolescents and children are categorized as overweight or obese. Overweight and obesity are conditions that have serious health and economic consequences (Finkelstein, et al., 2012; Finkelstein, Trogdon, Cohen, & Dietz, 2009; Wang Y., Beydoun, Liang, Caballero, & Kumanyika, 2008). Excess weight, particularly abdominal adiposity, is strongly associated with cardiovascular mortality (Coutinho, et al., 2011; Berrington de Gonzalez, et al., 2010; Bogers, et al., 2007; Després, Moorjani, Lupien, Tremblay, Nadeau, & Bouchard, 1990) and is thought to be mediated by cardiometabolic disorders such as dyslipidemia, insulin resistance and diabetes and hypertension (Cornier, et al., 2011; Després, et al., 2008; Klein, et al., 2004; Miller, Nori-Janosz, Lillystone, Yanez, & McCullough, 2005). It is also associated with several types of cancers, sleep disorders and stroke (Whitlock, et al., 2009). Despite being preventable conditions, the majority of U.S. adults today meet the clinical definition of overweight or obese (Centers for Disease Control and Prevention, 2012) and are therefore at increased risk for life-threatening health conditions. Based on the scientific evidence, there is critical need to address obesity with effective behavior change models that can be delivered en masse and sustained over the long term.

Over the last several decades, countless weight loss strategies have been utilized with mixed short and long-term results. Most efforts have focused on weight reduction,
using variations of calorie restriction or specialized dietary regimens promoted by the media. Medifast, Nutrisystem, Jenny Craig diet, and Slim Fast are a few examples of commercialized weight loss programs that advertise rapid weight loss. Others, like Weight Watchers, the Zone diet, the Atkins diet and the Ornish diet have combined dietary change with exercise and appear to be among the more successful efforts. Nicklas, Huskey, Davis & Wee’s (2012) review of weight loss methods found that meaningful weight loss of 5-10% was achieved by obese adults who ate less fat, exercised more, used prescription weight loss medications or participated in commercial programs. It is important to note that these findings reflect short-term outcomes and cannot be extrapolated to long-term maintenance of weight loss. Other weight loss approaches have taken note of successes in the tobacco and drug literature (Shahab & McEwen, 2009; Cobb, Graham, Byron, Niaura, & Abrams, 2011; Cunningham, 2012) and have utilized various components of these behavioral strategies to motivate change. These components include self-efficacy, self-monitoring, and social support. Still others have utilized media and call-in help lines as means of supporting behavior change (Anderson & Zhu, 2007; Czarnecki, Vichinsky, Ellis, & Perl, 2010). All of these efforts have provided further evidence of the many challenges that individuals face as they struggle to lose weight and improve health. They underscore the need for updated, contemporary approaches to behavior change.

One relatively newcomer in the behavior change field that has shown promising results is the use of technology as a form of personalized behavior motivation (Neve, Morgan, Jones, & Collins, 2010; McDoniel, Wolskee, & Shen, 2010). Generally
speaking, computer-based interventions appear to be effective for weight loss. A recent Cochrane Review of 18 internet based weight loss and maintenance programs (Wieland, et al., 2012) found that at 6 months, computer-based programs were more effective than usual care interventions, but less effective than face-to-face interventions in terms of weight loss. Although less effective than in-person interventions, the reviewers cite cost, convenience and reach as major advantages of internet-based approaches thereby deeming the internet a viable delivery method for these types of interventions. Other researchers caution against such generalizations, calling for more research evaluations that accurately reflect the efficacy of internet health promotion. Bennett and Glasgow (2009) suggest we move beyond the question of whether internet interventions work for health promotion. Rather, they emphasize the need to investigate the factors that influence the target population of such interventions, noting that the potential of this delivery method will not be realized until we better understand which features work for which outcomes, and for whom.

The current literature contains several salient studies done using specific technology features to target specific behaviors. For instance, pedometer and accelerometer studies have suggested a moderate and positive effect on health by increasing physical activity (Kang, Marshall, Barreira, & Lee, 2009; Bravata, et al., 2007). Personal digital assistants have been used to track dietary intake and have been associated with improved self-monitoring adherence and weight loss (Burke, et al., 2011; Beasley, Riley, Davis, & Singh, 2008). Brindel, Freyne, Saunders, Berkovsky, Smith and Noake (2012) examined features that were predictive of weight loss in overweight and
obese adults engaged in a technology oriented intervention and found that frequency of
weight monitoring and engagement in online social networking predicted weight loss, on
a separate basis. Their findings showed that frequency of self-recorded weight, using an
online weight tracker, was the most predictive of weight loss.

The present research explores a recent intervention that included multiple,
interactive technology components in overweight healthcare workers who were interested
in losing weight and improving health. The iWell randomized clinical trial was 6-month
weight loss and health improvement intervention conducted in 2010 in a healthcare
setting in Springfield, Oregon. Five hundred overweight adult healthcare workers were
enrolled and randomized into either a control (self-directed) group or an experimental
(technology-enabled) group for the 6-month intervention. Attrition was similar for both
groups (34%) resulting in a control group of 165 participants and an experimental group
of 168 participants that completed the 6-month intervention. The technology features
used by the experimental group included interfaced tracking instruments to upload data,
linkage to the iWell website, a personal homepage to monitor progress, and an exclusive
online social network that connected the technology-enabled participants. Biometrics
and biomarkers of control participants were compared to those of intervention
participants with weight loss as a primary outcome measure. Previous research has
reported results of the 6-month trial (Greene, Sacks, Piniewski, Kil, & Hahn, 2012),
finding the technology-enabled subjects had better health outcomes (weight loss and
increased physical activity) than the subjects in a self-directed control group.
Specifically, weight loss and activity patterns were greater for the technology-enabled
participants than the control participants (mean weight loss of 5 lbs versus 1.5 lbs, and 164% increase in walking minutes versus 47%, respectively). These results suggest a potential advantage to using multi-component interactive technology to facilitate health improvement in employees that work in a healthcare setting.

Technology is rapidly becoming a potent tool for behavior change but historically, has not been a staple of public health interventions (Bennett & Glasgow, 2009). Technology is a ubiquitous feature of modern life, permeating nearly every aspect of our daily activities including the way we communicate, the way we work, manage our finances and spend our leisure time. With two-thirds of U.S. adults overweight or obese, health professionals are exploring innovative strategies that utilize various technology components to address this rapidly advancing epidemic. Interactive technology is increasingly being used for behavior interventions but has not been fully explored for its potential to provide the infrastructure needed to support individual and population behavior change, especially with regard to weight loss interventions. Technologic features like interactive websites, text messaging and videoconferencing have been found to be effective in theory-based behavior change interventions but effects have been variable and warrant further study (Webb, Joseph, Yardley, & Michie, 2010).

As with the Boston example, it appears to take more than a web-based platform to mobilize the masses. There is a fast-advancing menu of technology features and approaches for health management including internet delivery platforms, wireless tracking instruments, mobile applications and online social networking options, most of which have mixed results at best (Wieland, et al., 2012; Khaylis, Yiaslas, Bergstrom, &
Gore-Felton, 2010). Websites like SparkPeople provide users with online “tools” aimed primarily at weight loss. Body sensors like FitBit and Nike Fuel Band track metrics and provide real time feedback for individual users. The emergence and popularity of smart phones and mobile devices has provided technology-enabled health and wellness opportunities through applications (apps) that can track health and fitness activities. Social media allows individuals and groups to share information and support each other through support groups, blogs, and online social networks. This myriad of options has created a growing interest in understanding how technology may influence health behavior (Riley, Rivera, Atienza, Nilsen, Allison, & Mermelstein, 2011).

Currently it is not known which stand-alone or combined technology features facilitate health improvement and for whom. For instance, results from the iWell study did not consider personal, clinical or technological factors that may have contributed to (or inhibited) success. According to a review of technology-based programs, Khaylis, Yiaslas, Bergstrom and Gore-Felton (2010) found that portable self-monitoring devices facilitated weight loss in some interventions. Others were successful with an internet-based counseling and group support format. The technological features used in each of the 21 studies reviewed by the researchers differed, making generalizations about multi-component approaches difficult. Further study is needed to understand why certain features work for certain people, and how best to design intervention efforts that incorporate one of more modes of technology.

Advances in health technology are occurring at a rapid pace. Health and fitness tracking devices, such as the BodyMedia Link, JawBone UP, and MotoActv have
become popular options for those who wish to lose weight and increase fitness, and have the financial means to purchase such wearable technology. Intended primarily for individual use, these gadgets are designed to facilitate health improvement through some of the same behavioral pathways as traditional in-person interventions by providing real-time, visual feedback. Commercially available web-based health improvement and weight loss programs like SparkPeople and Weight Watchers have drawn millions of followers seeking diet and lifestyle information. Mobile applications like Lose It! and MyFitnessPal help individuals record and track fitness and diet activities, and provide immediate and on-going feedback. Feedback, self-monitoring and website support are technology features that have been shown to facilitate engagement and health improvement (Shuger, et al., 2011). To a certain degree, today’s technology options have taken those features into consideration. However, a key component of successful behavior change programs is structured social support, and this is not a consistently integrated feature of commercial devices, programs or applications.

Social support has been studied extensively and has been shown to motivate behavior change, improve self-management and reduce negative sequelae associated with chronic conditions (Cohen & Janicki-Deverts, 2009; Cohen S., 2004; Uchino, 2004; Berkman L., 1995). Behavioral research has shown that the constructs of social support help reduce stress, anxiety, symptoms of depression, and reduce the likelihood of maladaptive behaviors such as drug and alcohol abuse (Glanz & Bishop, 2010). More recently, social support interventions have been shown to play an important role in internet-based options for weight loss (Hwang, et al., 2010; Pellegrini, Verba, Otto,
Helsel, Davis, & Jakicic, 2011) where shared purpose, convenience and anonymity are features of the program that participants favor. More research is warranted to understand how best to interface technology and behavioral interventions to optimize positive health outcomes.

In a modern context, the social support environment has been redefined by technology. Today, social ties often consist of friend connections that are made and maintained in cyberspace, on social network sites such as Facebook, Pinterest, and LinkedIn. These internet-based platforms allow millions of people to interact, share information and communicate with other individuals and communities at any time using mobile or desk top technology. Although not considered as strong as traditional relationships with trusted family member and friends (Gilbert & Karahalios, 2009), these online connections—often described as “weak” ties—still provide opportunities for support, motivation and accountability (Newman, Lauterbach, Munson, Resnick, & Morris, 2011). The rapid growth of online social networks (OSNs) has resulted in new ways of communicating, advertising and sharing information. The potential for using OSNs for health improvement interventions is great, particularly when combined with interactive health technology components.

Significance

The primary goal of this research is to explore how interactive technology, including online social networking, influences disease risk and health outcomes (particularly weight loss) in overweight adult healthcare workers. To date, few studies have examined intervention applications that involve multi-component interactive
technology and online social networking for short and/or long-term weight loss. This exploratory analysis will examine data from such an intervention that was done in 2010-2011 in Springfield, Oregon. The iWell trial was a 6-month randomized controlled study conducted in a healthcare setting. The iWell study enrolled overweight adult healthcare workers who were interested in losing weight and improving health. The results of the 6-month trial found that the technology-enabled subjects (n=168) had better health outcomes (weight loss and increased physical activity) than the subjects in a self-directed control group (n=165). In essence, weight loss and activity patterns were greater for the technology-enabled participants than the control participants. The preliminary results indicate a potential advantage to using multi-component interactive technology to facilitate health improvement in employees that work in a healthcare setting. What is not known is which variables predicted weight loss in the intervention participants. A closer look at the intervention data prompts several questions that may address the true nature of the associations between weight loss, physical activity, online social networking and the interactive platform. Were certain characteristics such as age, gender, or baseline disease burden predictive of weight loss? Were certain technology features such as utilization of the social network, activity tracking or weight monitoring predictive of weight loss? After the study ended, were weight loss and clinical biomarker changes different in the technology-enabled participants as measured from baseline to 6 month end of study and after one year follow up? How did perceptions of benefit, health status and self-monitoring habits correlate with longer term outcomes? These questions provide
the basis for the study hypotheses. Existing data is available to analyze these questions and will be used to test several hypotheses.

**Study Aims**

Using the data from 168 technology-enabled participants who completed the 6-month RCT and a subsample of these participants at one year post-intervention the following specific aims are proposed:

**Aim 1:** *Determine predictors of weight loss in overweight and obese healthcare workers who used multi-component interactive technology and online social networking in a 6-month weight loss intervention.* The purpose of this aim is to determine factors that were associated with participants who were most successful losing weight using the technology-enabled approach, as measured from baseline to 6-month study completion. I hypothesize that characteristics of gender, age, disease burden and use of technology features (activity uploaded, weight uploads, use of the OSN) will be predictive of weight loss.

**Aim 2:** *Determine longer term effectiveness of interactive technology and online social networking intervention one year after the 6-month intervention ended, and examine variables associated with maintained weight loss and health improvement.* This aim is designed to determine whether weight loss was maintained one year post-intervention and to examine the variables associated with weight loss maintenance, including qualitative variables such as perception of benefit, self-reported health status and current activity and weight-monitoring habits. Additionally, changes in risk markers for cardiovascular and metabolic disease will be examined to determine differences from
baseline to one year post-intervention. I hypothesize that weight loss will be maintained at one year post-intervention, and that certain variables will be associated with weight loss maintenance. I further hypothesize that clinically important differences will be detected in cardiovascular and metabolic risk markers at one year post-intervention.

Limitations of Study Approach

Examining the effectiveness of the iWell intervention retrospectively has some inherent limitations. The overall sample included healthcare workers who were interested in improving health. This resulted in a sample that consisted of primarily white females over the age of 50 that may have been more interested in health than a truly randomized sample. Beyond employment status, other characteristics of the sample such as socio-demographic status, education level, job position (clerical, clinical) were not known and therefore could not be factored into the findings of the study. Research questions focused on identifying predictors of weight loss in the technology-enabled group, therefore data from technology-enabled participants (n=168) who completed the intervention was used for analysis, limiting the ability to generalize findings beyond this population.

With respect to intervention design, there was no structured dietary component in the intervention arm of the iWell study, therefore the results may not be comparable to other studies that included such a component. Assessments regarding knowledge of obesity health risk indicators, perceptions of risk, and experience with self-monitoring technology and online social networking were not made and may have influenced findings of the study.
Another important consideration is that fact that although the intervention was based on an interactive technology platform, factors related to technology proficiency, experience and general interest were not assessed. At baseline, devices were checked for accuracy and participants were instructed on use. Beyond this point, any technical difficulties with the instruments, website or software were not documented. Although technical help was available, consistent and thorough data collection may have been compromised due to device malfunction, user error or other technical issues. As for using the online social network, communication activity was tracked only if a participant entered information into the network (“ friending”, commenting, posting). The number of passive views was not measured.

Lastly, the one year post-intervention assessments were added to the study protocol after the study ended, and included only intervention participants that completed the 6-month study. The one year post-intervention outcomes are derived from a subsample (n=48) of the intervention participants and may not truly reflect longer term outcomes for the intervention group as a whole. It is possible that a number of unknown factors may have influenced health indicators in the time between study completion and the one year follow-up. All technology-enabled participants who completed the 6-month intervention (n=168) were invited to participate within a 10-week time frame. The subsample of 48 was not randomized, and therefore results from this group may not be representative of the technology-group as a whole, at one year post-intervention.
Given these unique limitations, the results of this research should be interpreted with care, as they may not be generalizable beyond the source population.

Chapter 2 consists of a review of the scientific literature regarding obesity epidemic and the need for new weight loss approaches, how technology is being used to manage health, the role of theory and the importance of social support, and the promise of emerging technologies and alternate approaches for improving weight loss outcomes. Literature regarding these topics is reviewed in detail as related to specific aims 1 and 2 and in terms of relevance and adequacy for intervention development in today’s wired world. Using technology to improve population level approaches for an epidemic like obesity is dependent on identifying and understanding which features work for which outcomes and for whom. This review is intended to provide a framework for that understanding.

Chapter 3 is the methods section describing the data set, the data collection methods, study participants and protocol, and statistical analyses measures for Specific Aims 1 and 2. This chapter also summarizes the research analyses that were used for each study objective based on the variables of interest.

Chapter 4 presents results from each analyses. Specifically, this chapter reports results related to short and longer term weight loss among healthcare workers that participated in a 6-month technology and online social networking intervention, examining differences associated with age, gender, disease burden or utilization of technology features.
Chapter 5 presents a discussion of the findings, public health implications, limitations of the study, suggestions for future research and overall conclusions.
Chapter 2

Literature Review

Obesity and Health

An Epidemic of Obesity

Today, the vast majority of Americans over the age of 20 are overweight or obese (U.S. Department of Health and Human Services, 2013) and are at greater risk for weight related health issues. Since 1980, the prevalence of overweight has more than doubled, with concomitant increases in a variety of chronic, debilitating conditions. Obesity is strongly associated with the onset of cardiovascular disease, sleep apnea, certain cancers, arthritis and diabetes (Lavie, Milani, Artham, Patel, & Ventura, 2009; Burton, Foster, Hirsch, & VanItallie, 1985; Must, Spadano, Coakley, Field, Colditz, & Dietz, 1999). Obesity is considered a leading cause of death, attributed to 16% of all deaths in the U.S. (Jia & Lubetkin, 2010), surpassed only by tobacco use as the second greatest cause of preventable death in the United States. Projections are dire—the epidemic will march on as prevalence is expected to rise 33% in the next two decades (Finkelstein, et al., 2012).

Overweight and Obesity Defined

Kuczmarski and Flegal (2000) define overweight as “weight that exceeds the threshold of a criterion or standard reference value.” Reference values and criterion standards are not the same. Reference values refer to population distributions of weight measures while criterion standards refer to the relationship of weight to morbidity and mortality. This difference is important to note as it helps to distinguish whether weight measures are indicative of statistical distributions or health outcomes. In other words, not
every measure of excess weight is synonymous with poor health. Obesity has been described as excess body weight that is 20% or more over ideal weight and is often the point at which clinical treatment is advised (National Heart, Lung, and Blood Institute, 1998).

Body mass index (BMI) remains the most widely used, non-invasive classification for overweight and obesity and is determined by dividing weight in kilograms by height in meters squared (NHLBI, 1998). The World Health Organization (WHO) and the National Institutes of Health (NIH) have defined overweight as having a BMI between 25 and 29.9 kg/m\(^2\) and obesity as having a BMI greater than 30.0 kg/m\(^2\) (World Health Organization, 2012; U.S. Department of Health and Human Services, 2013). A BMI of 30 or greater has been associated with negative health conditions such as diabetes, lipid disorders, cardiovascular disease and hypertension (Bays, Chapman, & Grandy, 2007; Field, et al., 2001) and is therefore an important indicator of the health of a given population. Assessment of BMI is easy to perform and provides meaningful population level prevalence. As a stand-alone indicator, BMI does not distinguish between body fat and muscle mass and can thereby over- or under-estimate body weight. It should be noted that although BMI is widely used for population-level prevalence estimates, this method of weight categorization is limited in its ability to detect fat distribution on an individual basis, therefore it should be interpreted with care in the diagnostic setting (Romero-Corral, et al., 2008).
Statistic and Trends

Epidemiologic information on obesity in the U.S. is readily available due to ongoing public health surveillance efforts by the Centers for Disease Control and Prevention (CDC). State indicator reports, data, maps and trends are invaluable resources for analyzing public health issues like obesity. The Behavioral Risk Factor Surveillance System (BRFSS) and the National Health and Nutrition Examination Survey (NHANES) are two important sources of national obesity data (Centers for Disease Control and Prevention, 2012). Obesity prevalence has been extracted from BRFSS data for over 25 years from self-reported height and weight information. Since 1990, these data have been graphically depicted on yearly maps of the United States, using gradations of color to depict obesity rates for each state. As of 1990, data was available for all but a handful of states. At that time, the highest reported obesity rate was 14%, and only two gradations of color were needed to illustrate rates. Over time, the literal painting of the picture has been significantly transformed. Many familiar with the annual maps have seen the dramatic change in colors and shades, representing the rapid advancement of the epidemic across all states. Also noticeable on the maps are considerable variations between states, with higher rates seen in southern states as compared to west and northeast states. The 2010 map shows a grossly different picture from the 1990 map, with no states reporting a prevalence less than 20% and the vast majority of the states reporting prevalence rates of 20% to >30%.

The alarming rate of progression has resulted in ambitious but largely ineffective efforts to curb the trend. The Healthy People Initiative (U.S. Department of Health and
Human Services, 2013) began in 2000, and implemented policy based, educational and environmental strategies to improve population health over 10-year periods. The effort specifically targeted obesity in the 2010 objectives, stating a goal of lowering the obesity prevalence rate to 15%. No state met this goal, and the rate of obesity continued to climb. Despite recent reports of obesity rates plateauing in certain populations (Rokholm, Baker, & Sørensen, 2010), the majority of U.S. adults remain overweight or obese and are at risk for health conditions related to excess weight. A 2010 report from the National Center for Health Statistics estimated 65% of American adults to be overweight, and over one third obese, based on measured data (Ogden, Carroll, Kit, & Flegal, 2012). In addition, the prevalence of morbid obesity, defined as 100 pounds overweight or a body mass index equal or greater than 40% (National Heart, Lung, and Blood Institute, 1998), is on the rise, with an estimated 5% of U.S. adults over the age of 20 in this category.

The Costs of Obesity

The collective and individual excess weight has resulted in health and economic burdens never before seen (Wang, McPherson, Marsh, Gortmaker, & Brown, 2011). The recent Trust for America’s Health report (Levi, Segal, St. Laurent, Lang, & Rayburn, 2012) estimated the current annual cost of obesity to be between $147 and $210 billion. This estimate is based on the medical costs related to treating preventable obesity-related diseases and conditions. Overweight and obesity are associative and independent risk factors for a number of costly and debilitating chronic conditions including metabolic disorders, hypertension, hyperlipidemia, and coronary heart disease (Kopelman, 2007).
Obesity has been linked to premature death, disability and at least 20 co-morbid conditions, including type 2 diabetes, several types of cancers, sleep apnea, asthma, arthritis, gall bladder disease and insulin resistance (Guh, Zhang, Bansback, Amarsi, Birmingham, & Anis, 2009; Kahn & Flier, 2000), creating staggering health and economic burdens. The economic costs alone are projected to be well over $900 billion dollars in 2030 (Wang, Beydoun, Liang, Caballero, & Kumanyika, 2008) making obesity arguably the most important health crisis of our time.

The direct cost of obesity is related to excess healthcare expenditures while the indirect cost refers to lost productivity and resources due to health conditions (Colditz, 1992). Both must be considered when discussing the overall economic burden of obesity. Costs of obesity are reported in various ways, and inconsistently in the current literature. Globally, Withrow and Alter (2011) estimate obesity to cost between .7 and 2.8% of a country’s total healthcare expenditures, while Cawley and Meyerhoefer (2012) calculate a figure closer to 21% for the United States. Wang, McPherson, Marsh, Gortmaker and Brown (2011) project costs attributed to obesity to double every 10 years, equating to 16-18% of all annual healthcare expenditures by 2030. Put simply, when a high percentage of the population is overweight or obese, more health services are used, and treatment costs for obesity-related diseases like type 2 diabetes and cardiovascular disease cost more than they would in a normal-weight population (Wang, McPherson, Marsh, Gortmaker, & Brown, 2011). Individual level costs are staggering as well. Withrow and Alter (2011) estimate an obese person to spend 30% more on healthcare expenditures compared to a normal weight counterpart.
A shortened life expectancy is another consequence of obesity that impacts cost and lost productivity estimates. The life expectancy of an obese person has been reported to be below that of a smoker (10 years) yet significantly high at 7 years (Reuser, Bonneaux, & Willekens, 2009; Muennig, Lubetkin, Jia, & Franks, 2006), strengthening the argument for obesity prevention measures as a means of reigning in costs and maximizing productive years of life.

**Populations Affected**

Obesity prevalence in the U.S. has increased across all age, gender, racial and ethnic groups but affects some groups more than others. Prevalence among all adults over the age of 20 is currently estimated to be 35% based on measured data (Centers for Disease Control and Prevention, 2012). However, differences are seen across adult age groups, with adults over the age of 60 more likely to be obese (Ogden, Carroll, Kit, & Flegal, 2012). According to NHANES 2009-2010 data (Centers for Disease Control and Prevention, 2012), prevalence rates do not differ significantly according to gender, although more women have extreme obesity as compared to men (Flegal, Carroll, Kit, & Ogden, 2012). As for children and adolescents, one third of children are overweight and an estimated 1 in 6 children are obese (U.S. Department of Health and Human Services, 2013).

Racial and ethnic disparities in obesity have been noted among women and children (Wang & Beydoun, 2007; Flegal, Carroll, Ogden, & Curtin, 2012), and differences have been observed in some minority and lower socioeconomic status (SES) groups (Wang & Beydoun, 2007). Non-hispanic black women and children, Mexican
American women and children, and low SES men, women and children are disproportionately affected. Nationally representative data from the CDC (2012) indicate that differences have not changed over time, and the following disparities persist: For both men and women, Blacks and Mexican Americans have higher prevalence of obesity than whites, black women have higher obesity rates than White women, and racial and ethnic differences remain, even when income differences are controlled.

Education and income level disparities exist as well (Ogden, Lamb, Carroll, & Flegal, 2010). Men demonstrate similar obesity rates regardless of education, but women with college degrees are less likely to be obese than women with lower educational attainment. As for income level, lower income women are more likely to be obese than higher income women, while higher income non-Hispanic black and Mexican American men are more likely to be obese than lower income cohorts.

As mentioned earlier, regional differences in the distribution of obesity in the U.S. are also reported. The BRFSS maps referenced above show a distinct geographic variation with obesity prevalence, which appears concentrated in the south. Generally speaking, these areas report the highest prevalence of obesity. In 2011, Mississippi, Alabama, West Virginia, Louisiana and Oklahoma reported higher than 30% obesity prevalence, according to self-reported data. Conversely, New England states and Western states had the lowest rates of obesity.

*Risk Factors for Obesity*

Obesity is thought to have a genetic association (Stunkard, Harris, Pedersen, & McClearn, 1990; Coady, Jaquish, Fabsitz, Larson, Cupples, & Myers, 2002) but most
researchers point to behavioral and environmental factors to explain the rapid rise in obesity prevalence (Philipson & Posner, 2003; Cutler, Glaeser, & Shapiro, 2003). In discussing the economics of obesity, Finklestein and Strombotne (2010) identify food consumption and energy imbalance as significant predictors of obesity. In simple terms, eating too much and exercising too little is likely to result in excess weight. Food availability is thought to be part of the problem. Relative to other goods and services, overall food prices have dropped in the last 30 years. At the same time, these economists explain that healthier foods have become more expensive and calorie-dense foods have become more affordable, resulting in an excess daily caloric intake of 80 calories for men and over 300 calories for women. The authors further cite decreases in energy expenditure in the workplace and in leisure time activities as reasons for energy imbalances that lead to obesity.

The role of the environment as an obesity determinant may be less understood but has long been of interest to researchers (Michael & Yen, 2009; Berke, Koepsell, Moudon, Hoskins, & Larson, 2007; Hill & Peters, 1998). Many point to the built environment (physical infrastructures, land use patterns, transportation systems) as being a predictor of food and activity choices that lead to energy imbalances, especially if conditions are such that 1) there is not a supermarket nearby 2) high calorie foods are the most convenient and affordable, and 3) engagement in physical activity is optional or discouraged (Li, Harmer, Cardinal, Bosworth, & Johnson-Shelton, 2009; Bray & Champagne, 2005).

Though debate may ensue about the origins of obesity, most researchers agree risk factors for the condition are multifactorial, and should be addressed from an
ecological perspective. They include known, modifiable individual factors as well as environmental factors that should be carefully considered in the design and implementation of weight loss interventions.

*Biomarkers of Health and Disease Related to Obesity*

Knowledge of the biomarkers of obesity may help in identifying individuals who are at risk (Musaad & Haynes, 2007). Obesity biomarkers include but are not limited to absolute body weight, waist circumference, BMI, insulin resistance markers (triglyceride/HDL ratio, fasting blood glucose and glycosylated hemoglobin), plasma lipid levels and resting blood pressure. Collectively, these biomarkers can lead to life-threatening conditions such as heart disease, diabetes, and stroke. “Syndrome X” and “metabolic syndrome” are terms that have been used to describe the clustering of these risk factors (Grundy, Brewer, Cleeman, Smith, & Lenfant, 2004). Most people with this syndrome are considered insulin resistant, and at high risk of developing type 2 diabetes. The biomarkers related to obesity are not difficult to obtain, especially in a healthcare setting. They can be measured through standard lab procedures and measurements done by trained personnel. Importantly, these markers can be modified by diet and exercise (Eckel, Grundy, & Zimmett, 2005; Esposito, et al., 2003) and can be monitored over time for optimal management.

In the year 2000, Astrup and Finer used the term “diabesity” to describe the close association between obesity and type 2 diabetes. In their review of the etiology of type 2 diabetes, they cite the combination of obesity and abdominal fat as being responsible for 80-90% of cases. Today, type 2 diabetes continues to be a target for early intervention...
efforts aimed at blood glucose control. Diabetes is a metabolic disorder in which the body is unable to absorb circulating glucose properly. Chronic exposure to elevated levels of blood glucose can render cells incapable of using circulating glucose for energy, and over time can damage the nervous and circulatory systems (Astrup & Finer, 2000). Plasma blood glucose is the biomarker indicative of the glucose concentration in the blood at any given time. A fasting level above 100mg/dl is considered “pre-diabetic” and a level above 126mg/dl is diagnostic of diabetes (Diabetes Care, 2013). Another biomarker used to diagnose diabetes is glycosylated hemoglobin (HbA1c), which averages blood glucose levels over the past 3 months (Medline Plus, 2013). The American Diabetes Association has defined a normal HbA1c as below 5.7%. Both plasma blood glucose and HbA1c can be modified. The Look AHEAD weight reduction trial followed over 5000 individuals with type 2 diabetes, finding that plasma blood glucose and HbA1c levels can be normalized through lifestyle changes that result in weight reduction (Pi-Sunyer, et al., 2007).

Obesity is associated with higher cardiovascular risk, negatively affecting lipid levels by increasing total and LDL cholesterol, decreasing HDL cholesterol and increasing triglycerides (American Heart Association, 2013). Miller, Nori-Janosz, Lillystone, Yanez & McCullough (2005) describe the “dyslipidemia of obesity,” characterized by low HDL levels, high triglyceride levels and several other small particle lipid abnormalities, all providing the perfect environment for atherogenesis. Weight loss has been shown to lower total and LDL cholesterol, reduce triglycerides and increase
HDL levels (Goldstein, 1992; Dansinger, Gleason, Griffith, Selker, & Schaefer, 2005; Dattilo & Kris-Etherton, 1992; Batsis, et al., 2007).

**Projections**

Until the 1980’s, obesity prevalence rates were fairly stable (Flegal, Carroll, Kuczmarski, & Johnson, 1998). For example, in the 1960’s, the average American male weighed 168 pounds and the average American female weighed 143 pounds (Cutler, Glaeser, & Shapiro, 2003). In the span of just thirty years, average weight has increased to 195 for males and 166 for females (Ogden, Fryar, Carroll, & Flegal, 2004). In the same span of time, obesity rates have tripled for school-aged children.

The trend in obesity prevalence and costs is expected to continue. Today, 35% of those who are overweight are obese, and this is projected to increase to 44% by 2030 (Finkelstein, et al., 2012). A recent report released by the Trust for America’s Health and the Robert Wood Johnson Foundation estimates by 2030, all 50 states will have an obesity rate over 44% if the prevalence trends continue (Levi, Segal, St. Laurent, Lang, & Rayburn, 2012). With this saturation, obesity related health and economic costs are projected to increase as much as 35% in some states. On a promising note, the report also projected the health and economic savings if states were to lower BMI rates just 5%. With this modest reduction, millions of cases of type 2 diabetes, cardiovascular disease, cancers and arthritis would be prevented, equating to billions of dollars saved on unneeded health care expenditures. The report further states the importance of preventive efforts, stressing the need for nutrition, physical education and marketing policies that specifically address childhood obesity prevention.
Changing Difficult Behaviors—Lessons Learned

The Resistant Nature of Weight Loss

Although modifiable conditions, treatment strategies for excess weight and obesity have not proven to be effective in the long term (Wing & Phelan, 2005; Curioni & Lourenço, 2005; Anderson, Konz, Frederich, & Wood, 2001). Numerous studies indicate that clinically significant weight loss is possible, but the majority of losers do not maintain weight loss beyond one year (Witham & Avenell, 2010; Kraschnewski, et al., 2010; Svetkey, et al., 2008; Wing & Phelan, 2005; Gorin, Phelan, Hill, & Wing, 2004). Individuals who lose weight are likely to regain a third of that weight within the first year, and will return to a baseline weight within 3-5 years (Wing, Tate, Gorin, Raynor, & Fava, 2006). Some research has pointed to treatment adherence, cost, and lack of theoretic understanding as major reasons for poor long-term outcomes (Winnet, Tate, Anderson, Wojcik, & Winett, 2005). Investigators using longitudinal data have found behavioral and psychosocial factors have been shown to be predictive of weight regain (Butryn, Phelan, Hill, & Wing, 2007; Wing, Tate, Gorin, Raynor, & Fava, 2006). These include changes in physical activity, television viewing, dietary fat intake, self-weighing habits, depressive symptoms, and changes in restraint and hunger. Byrne, Cooper and Fairburn (2003) suggest certain psychological variables explain weight regain in obese individuals. Based on qualitative data, the investigators found mood, self-image, dichotomous thinking, and lack of vigilance to be associated with weight regain in previously successful weight losers. According to other researchers, reasons for the refractory nature of weight loss maintenance go beyond behavioral factors and include
such complex determinants as genetics and metabolic disorders (Kraschnewski, et al., 2010).

As some research has suggested, maintained weight loss is possible, especially among those that adhere to structured exercise, diet and self-monitoring behaviors (Schaar, Moos-Theile, & Platen, 2010; Thomas & Wing, 2009). Interventions that have been successful have focused on motivational and behavioral factors such as exercise regulation, frequent self-weighing, goal-setting, social support and self-efficacy, and dietary therapy (Turk, et al., 2012; Butryn, Phelan, Hill, & Wing, 2007; Wing, Tate, Gorin, Raynor, & Fava, 2006; Lang & Froelicher, 2006; Elfhag & Rössner, 2005; Silva, et al., 2011). Numerous investigations have associated successful weight loss to economic incentives (John, Loewenstein, Troxel, Norton, Fassbender, & Volpp, 2011; Arterburn, et al., 2008; Volpp, John, Troxel, Norton, Fassbender, & Loewenstein, 2008) and the use of activity tracking devices, such as pedometers and accelerometers (Catenacci, Grunwald, Ingebrigtsen, Jakicic, McDermott, & Phelan, 2010; Goodpaster, et al., 2010; Khaylis, Yiaslas, Bergstrom, & Gore-Felton, 2010; Buis, et al., 2009; Bravata, et al., 2007; Richardson, Newton, Abraham, Sen, Jimbo, & Swarz, 2008). Previous research has suggested that short-term weight loss can be accomplished, but sustained weight loss is a challenge that continues to perplex medical practitioners, researchers and behavioral scientists alike. Understanding the multitude of lifestyle and motivational factors that influence success or failure in weight loss interventions and developing effective, sustainable strategies has become a national health priority. Alternate, multifaceted and widely scalable approaches are needed to improve weight loss efforts.
Technology may play an important role, as it has permeated nearly every aspect of modern life, including health management efforts and social activities.

*Weight Loss and Health Improvement*

Even modest amounts of weight loss are beneficial to health. Though achieving “ideal” weight is the goal of many weight losers (Foster, Wadden, Vogt, & Brewer, 1997), reductions as modest as 3 to 5% have been shown to modify and in some cases eliminate risk factors associated with obesity (Blackburn, 1995; Donnelly, Blair, Jakicic, Manore, Rankin, & Smith, 2009). Based on meta-analyses reviews and evidence-based clinical reports, the Institute of Medicine, the Centers for Disease Control and the National Institutes of Health have endorsed “modest” weight loss of 5 to 10% as beneficial to health, with particular reference to a reduction in cardiovascular risk (National Heart, Lung, and Blood Institute, 1998). Overweight persons who are intentionally trying to lose weight should be encouraged by the fact that any amount of weight loss can be beneficial to health, but for at-risk overweight persons, the directive should be more imperative.

Other researchers point to the magnitude of weight loss as they key, especially for those already at risk—type 2 diabetics (Wing, et al., 2011; Wadden, et al., 2012). In an observational analysis of over 5000 type 2 diabetics in the Look AHEAD study (Action for Health in Diabetes) the investigators found that at one year, more weight loss resulted in more clinically significant cardiovascular risk reduction. Participants who lost 5 to 10% of initial body weight were more likely to demonstrate improvements in glucose control, lipids and blood pressure as compared to those who lost less than 5%. In
addition, those that lost more than 10% of initial body weight showed greater improvements in the same cardiovascular risk markers. Results support modest weight reduction as health beneficial, but provide strong rationale for greater, sustained weight loss in persons already at risk.

Similarly, the results from the Diabetes Prevention Program (DPP) found weight loss to be particularly effective in delaying onset or avoiding manifestation of type 2 diabetes in at-risk adults. The DPP followed 3200 overweight adults who were at risk for type 2 diabetes and found a 58% reduction in risk in those that made lifestyle changes (diet and exercise) with consequent weight loss (Knowler, et al., 2002). Cardiovascular risk reduction was also noted through improvements in HDL cholesterol, triglycerides, blood glucose and blood pressure, which were greatest in the lifestyle intervention group as compared to the placebo group or the pharmacologically treated group (Goldberg, et al., 2009). Of note, 45% of the study participants represented minority groups, which are known to be disparately affected by diabetes. Since nearly 24 million people in the U.S. have diabetes, and 95% of the cases are type 2, these findings have important implications for public health strategists. In essence weight loss could prevent millions of people in the U.S. from suffering the health and economic consequences associated with diabetes.

**New Directions—Emerging Technologies and Interactive Approaches**

*Weight Loss Methods using Technology*

Weight loss interventions have traditionally been delivered using a face-to-face format with emphases on diet, exercise and behavior therapy. The general treatment
structure typically includes weekly in-person education and skill-building sessions for 4 to 6 months (Wadden & Butryn, 2003). With this approach, time constraints, costs and other perceptual barriers may have limited participation (Polzien, Jakicic, Tate, & Otto, 2007). Web-based weight loss interventions are alternate delivery systems that are becoming increasingly common and have been an area of interest for researchers for years.

An early study by Harvey-Berino, Pintauro, & Gold (2002) was one of the first to examine the feasibility of using the internet to conduct a weight loss maintenance study. Obese adults completed a 15-week weight loss intervention and were then followed for a 22 week maintenance period. For the intervention period, subjects were either randomly assigned to a therapist-led intervention, a computer-based intervention or a control group. Therapist-led and internet intervention groups each met twice weekly and both used the same educational materials. Although the therapist-led participants were more likely to show up for meetings, there was no difference between the two groups in amount of weight loss, overall attrition or the number of peer support contacts that were initiated. The results from this study affirmed the use of the internet as an alternate delivery method for weight loss efforts.

Brindal, Freyne, Saunders, Berkovsky, Smith and Noakes (2012) conducted a 12-week web-based weight loss intervention that was entirely automated and contained no in-person contact to determine factors predictive of weight loss as well as retention. Participants were randomized into an information-only based group, a group that used an online social network or a group that included the online social network and personalized
dietary counseling. All aspects of study participation were done online. Attrition at the end of the intervention was abnormally high (94%), and overall site usage was low, ranging between 3.4 and 6 days of access throughout the 12 week period. Although website usage was low across all groups, the difference was found to be statistically significant. Overall, the completers lost an average of 2.76% body weight. Weight tracking was the most frequent feature used by all groups, and was predictive of weight loss. In addition, age and initial BMI were associated with use of the weight tracker. Use of the social network (only 14% of the sample used the OSN) and the meal planner was not associated with weight loss. Despite a design that included different levels of support and personalization, this approach had little effect on participant retention. In addition, the availability of multiple interactive features did not improve the odds of weight loss, leaving the investigators to conclude that more research is needed to understand factors associated with engagement in web-based interventions.

Whether for commercial or clinical programs, the internet has become a viable tool for conducting weight loss activities. Evaluating the efficacy of technology-based weight loss programs is a relatively new area of research, especially in the primary care environment. Research thus far has focused on outcomes relative to delivery methods (face-to-face versus internet-based), behavioral modification, and self-monitoring. In general, the internet appears to have great potential for health improvement efforts such as weight loss. For example, Appel et al, (2011) found weight loss outcomes in participants in a remote support (web-based) intervention to be similar to weight loss outcomes in a group (face-to-face) intervention, both supported by primary care
physicians. Though short and longer term weight loss was demonstrated in these highly selected patients, it is not known if certain personal and design elements predicted success.

A Cochrane review of internet-based weight loss interventions concluded that interactive computer-based weight loss interventions were more effective than usual care interventions but not as effective as in-person interventions in terms of weight loss and weight maintenance (Wieland, et al., 2012). For this review, weight loss and weight loss maintenance studies were included, with durations that ranged from four weeks to 30 months. For short and longer-term weight loss, computer-based interventions demonstrated greater weight loss than minimal interventions but less than in-person interventions. The authors acknowledge the need for more study in this area, as the overall weight loss differences were modest and have questionable clinical significance. Findings from this review are also limited by relatively small number of studies that met review criteria (a total of 18) and the fact that some of the studies were over a decade old.

Pellegrini et al (2010) compared a technology-based system and an in-person weight loss intervention and found the technology-based system to be a viable alternative to traditional face-to-face formats. The study included 51 overweight adult subjects (mean BMI 33.7 kg/m²) who were randomized into a standard behavioral program, a standard behavioral program plus a technology-based system, or a technology-based system only. The standard behavioral program included weekly behavioral therapy sessions that emphasized self-monitoring, exercise and eating behaviors. The technology-based system included a wearable sensor that tracked activity and provided
real-time feedback via an interactive website. All groups underwent calorie-restricted eating and progressive exercise programming. Of interest, retention rates differed significantly among the groups, with the standard behavioral program plus technology demonstrating a 100% retention rate. Weight loss outcomes at 6 months were greatest for those that were in the standard behavior program plus technology, as compared to weight loss in the standard behavior program group or the technology only group. The findings suggest an additional weight loss of 2kg was attributed to the combination of using the technology and engaging in weekly behavioral therapy, leading the authors to conclude that the use of technology may provide additional short-term benefits in weight loss interventions.

The internet has fast become an acceptable alternative to in-person health improvement interventions and the management of chronic conditions, especially diabetes. Early researchers deemed the approach promising when they used web-based technology to assist with a diabetes self-management program (McKay, Feil, Glasgow, & Brown, 1998). In a 10-week period of time, 111 diabetics accessed the website more than 21,000 times, most commonly viewing the pages for social support and diabetes information. With wide accessibility and 24-hour/day availability, the users revealed high satisfaction with the service and the internet was deemed a feasible option for diabetes self-management, coaching and education programs.

Using an internet-mediated approach, Richardson, et al. (2007) assessed a physical activity intervention in persons with type 2 diabetes to look at differences between structured and lifestyle programs that both focused on increasing steps per day.
The structured program focused on bouts of activity rather than total steps accumulated. For six weeks, pedometers were worn by all subjects and were uploaded to a website that provided step count feedback and automated messaging. Both groups increased steps per day, but the lifestyle subjects were more satisfied with the intervention and wore the pedometer more often. This study may be useful when considering web-based physical activity intervention designs, particularly for specific chronic condition populations.

Lifestyle oriented internet interventions are becoming more commonplace and have been employed in interventions targeting physical activity behaviors (King, Ahn, Oliveira, Atienza, Castro, & Gardner, 2008; Norman, Zabinski, Adams, Rosenberg, Yaroch, & Atienza, 2007; Atienza, Oliveira, Fogg, & King, 2006; Davies, Spence, Vandelanotte, & Caperchione, 2012) and promoting weight loss (Binks & van Mierlo, 2010; Harvey-Berino, Pintauro, & Gold, 2002). With wide accessibility, 24-hour availability and the inherent connectivity to other users, current studies support using virtual environments to engage individuals in health management activities (Bennett & Glasgow, 2009). Access is not thought to be a barrier, as an estimated two-thirds of U.S. adults use the internet on a regular basis (Madden & Zickuhr, 2011). This medium of communication and information dissemination has captured the attention of many social and behavioral scientists who believe that when people are connected their health is connected (Smith & Christakis, 2008).

Technology-Based Interventions and Target Populations

Numerous studies have examined the use of physical activity trackers to motivate behavior change in target populations, such as older adults. Two noteworthy studies
indicate the general acceptance of such technology in the older adult demographic. In one such study, older underactive adults were instructed to monitor their physical activity levels using personal digital assistants (PDA’s) while being provided with feedback, goal-setting and support over an 8-week period of time (King, Ahn, Oliveira, Atienza, Castro, & Gardner, 2008). After 8 weeks, those using the PDA’s reported both greater caloric expenditure and increased minutes of exercise than compared to the control group who were given standard written activity and education materials.

In another study, Atienza, Oliveira, Fogg, & King (2006) studied the use of electronic diaries to track physical activity in adults over the age of 50. The primary objective of the study was to examine whether the use of such technology would be acceptable and increase exercise adherence in the study population. Despite most subjects never having used an electronic diary, over 80% reported enjoying using the diary and over 70% reported enjoying answering all of the health questions associated with the diary. According to the authors, these findings merit additional study regarding the use of technology to promote physical activity.

Findings from University of Michigan’s internet-mediated Active U study demonstrate that social support (team membership) is associated with meeting physical activity goals, a primary objective of the study (Buis, et al., 2009). This study was designed to promote physical activity during the winter months. Over 7500 university staff and graduate students participated, the majority between the ages of 18 and 59 years. The intervention was determined a success overall, as 79% of those enrolled logged in data at least once during the 8-week study period. Of interest is the fact that older, more
overweight participants were more likely to meet weekly activity goals, and the average rate of meeting goals was higher if a participant was on a team as compared to those that participated individually.

Web-based weight loss approaches have been used in other target populations as well. To promote weight loss in women who were at increased risk of breast cancer, investigators tested a web-based model that used self-monitoring tools to set goals and record daily activities and food intake versus a diet-instruction only comparison group (Cadmus-Bertram, Pierce, Patterson, Ojeda-Fournier, Newman, & Parker, 2011). Over the course of the 12-week intervention, participants randomized into the technology arm lost more weight and increased physical activity as compared to the diet-instruction only participants. In addition, technology-arm participants who described the website as “helpful” lost more weight as compared to those who rated it as “not helpful.” This pilot study was small (50 subjects) but had several pertinent findings with regard to using technology to support weight loss efforts in an adult population. The average age of the subjects was 60.9 years, indicating technology proficiency and acceptance in a targeted, older adult population.

*Healthcare Workers and Health Improvement Interventions*

For several reasons, healthcare environments are ideal targets for health improvement interventions. Over 18 million people are employed in the healthcare field making it one of the largest and most dynamic sectors of the U.S. economy (United States Department of Labor, 2012). Many healthcare organizations are already heavily invested in technology, utilizing it for electronic record documentation, communication,
and internet services. Worksites with such technological infrastructure are likely to have communication and education channels that can facilitate programs and messages to promote healthy behaviors. Healthcare organizations are typically stable work environments, employing allied, medical and administrative personnel that are often viewed as models for health and wellness (Lemon, et al., 2010). Though complex systems, healthcare organizations employ a large segment of the U.S. population, are stable, and have embraced the use of technology in a variety of ways.

Somewhat ironically, the healthcare environment has some of the highest rates of workplace injury and illness (United States Department of Labor, 2012). Overweight and obesity rates of healthcare employees mimic the general population and are thought to be associated with unique work demands (shift work) and stressors inherent in a healthcare setting (Miller, Alpert, & Cross, 2008). Healthcare workers may be assumed to have knowledge about good health behaviors but in reality, they may not practice what they preach. A phone survey done by the CDC in 2008 and 2010 included over 21,000 self-identified “direct patient care” health providers (Helfand & Mukamal, 2012). In the sample, 18% identified as smokers, and 64% reported being overweight. Twenty-five percent reported no physical activity in the last 30 days. In addition, the female health care workers over the age of 50 were 13 times more likely to have skipped breast cancer screening than the non-health care workers surveyed. Results of the survey are surprising yet informative and underscore the need to address this important demographic. The results speak to the challenge healthcare workers face as they are not exempt from the prevalent health issues of our time. To best model behavior—practicing what they
preach—the healthcare demographic appears to be an appropriate target for health improvement interventions.

In 2004, the National Heart, Lung and Blood Institute launched a special initiative called Overweight and Obesity Control at Worksites, funding seven worksite projects that included 114 worksites and nearly 48,000 employees. Each project used a socio-ecological model for health promotion, including environmental and individual-level approaches to increase physical activity and improve dietary intake (Pratt & Lemon, 2007). The Step Ahead Trial was part of the initiative and included 899 employees of 6 hospitals in the central Massachusetts area. Designed to prevent weight gain by promoting organization and social norms, the intervention used strategies to support an environment conducive to healthy eating and physical activity (Lemon, et al., 2010). These strategies could be seen in the cafeteria where healthy menu options were offered as well as in physical spaces like stairwells and walking paths that help promote physical activity. Like most healthcare settings, the majority of participants were females. Sixty-five percent of the participants had a BMI over 25 kg/m². The primary outcome was change in BMI at 12 and 24 month follow up intervals. Results with regard to weight gain prevention were not encouraging, as no intervention effects were seen at either time interval. Importantly, the intervention did result in improving perceptions of organization commitment to employee health and wellness even though perceptions of normative behavior were not changed. The authors note that these changes take time, and perhaps require different design elements for worksites that paradoxically want to offer health and
wellness opportunities but have productivity goals that prohibit time and flexibility to participate.

**Web-based Social Support and Health**

As seen in a variety of different investigational formats, socially connecting those who share a common goal appears to enhance motivational factors and favorably influence weight loss efforts. Today, social connections commonly occur through online social networks (OSNs), where users can connect to other users and communities with “the click of a mouse”. Online social networking is currently on the rise with an estimated 69% of adult internet users regularly accessing one or more sites (Brenner, 2012). Facebook is perhaps the most well-known OSN with an estimated 800 million users globally (Up Creative, Inc., 2013). Online social networks like Facebook allow individuals to publicize and create their own connections, building cultures that would not otherwise be realized (Boyd & Ellison, 2007). “Friendships” and linkages are typically initiated by a user who formally requests the connection which, in turn, must be accepted in order to be activated. The OSN member can then view, post and comment on the network at will, and can also control the sharing of information through customizable privacy settings.

Recent attempts at integrating wellness interventions into existing OSN’s have been considered beneficial but in need of design refinements regarding network scope and scale (Munson, Lauterback, Newman, & Resnick, 2010). Leveraging this connectivity with health improvement web-based applications could prove to be a highly effective, contemporary public health approach in today’s increasingly wired world.
(Khan, Fleischauer, Casani, & Groseclose, 2010), where users already have membership in communities that share health information.

**Components of Technology-Based Weight Loss**

Addressing the fact that we are becoming increasingly reliant on technology, targeted research efforts are exploring the interface between technology and traditional behavior change strategies. In one such analysis, Khaylis, Yiaslas, Bergstron and Gore-Felton (2010) conducted a qualitative review of technology-based weight loss interventions that occurred in the last ten years. Twenty-one experimental studies that used one of more components of technology were included in the review. The review found the following five components crucial to successful internet-based short-term weight loss intervention design: self-monitoring, computerized counselor feedback, social support, use of a structured program, and use of an individually tailored program.

For **self-monitoring** tasks, technology simplifies the process with wireless transmittal features that automatically record data points such as weight and physical activity. In addition, tracking dietary intake and calories is possible through online sites and mobile devices, replacing traditional time-consuming pen and paper methods. Technology facilitated self-monitoring allows for an element of privacy, continuous data streaming, and ease of use, especially with body monitors that are worn daily. **Counselor feedback** encourages and reinforces behavior, and online interactions have been shown to be as effective as in-person interactions (Hunter, et al., 2008) and are usually more time-efficient and convenient. Technology provides countless possibilities for leveraging **social support** through chat rooms, forums, and online networks. Weight loss
interventions that include online social support have higher utilization rates and better weight loss outcomes (McConnon, et al., 2007). *Structured programs* increase accountability and adherence by requiring certain deliverables, whether it be food or exercise diaries, or uploaded data. Finally, programs that are *individually tailored* have higher adherence rates and greater weight loss. Using technology to communicate and monitor individual goals has been done via text and email messaging (Hurling, et al., 2007).

Specific technology features have been found to be associated with engagement and utilization of interactive web-based weight loss interventions. Neve, Morgan, Jones & Collins (2010) conducted a review of 18 web-based weight loss interventions that were conducted between 1995 and 2008. These interventions used a variety of interactive features, with weight loss as the outcome of interest. Comparisons between studies were limited due to differences in interactive features that were used, study duration, and other methodological issues. The reviewers found only four meta-analyses to be comparable in terms of weight change associated with technology feature utilization and, ultimately, could not draw any conclusions related to weight loss associated with specific feature use. More recently, participants in a 12-week web-based weight loss study by Brindal, Freyne, Saunders, Berkovsky, Smith and Noakes (2012) had access to a variety of technology tools including an online social network, a meal planner, and weight and activity trackers throughout the study period. Only use of the weight tracker was predictive of weight loss and other features like the OSN were sub-optimally used or not used at all. Alternatively, an internet weight loss study by Binks and van Mierlo (2012)
found participants to be more likely to use interactive self-assessments than weight or activity trackers.

Hybrid approaches that use interactive technology and in-person support may also be important components of web-based interventions. The Weight Loss Maintenance trial (Hollis, et al., 2008) was a two-phased intervention for overweight persons with a BMI of 25-45 kg/m². The first phase consisted of weekly group sessions that focused on increasing physical activity (with a goal of 180 minutes per week), decreasing caloric intake, and weight loss. In addition, the behavioral constructs of motivation, support, problem-solving and relapse prevention were emphasized during this phase. This 6-month phase consisted of 1685 ethnically diverse, at-risk participants from multiple participating sites. Results from the first phase were impressive— the retention rate was 92% and 69% of the participants lost 4kg or more. In phase Two, 1032 participants were randomized into three groups: a self-directed group that had minimal intervention, an interactive technology group that used an interactive website, and a personal contact group that received monthly contact with an interventionist. The goal of this phase was to support weight loss maintenance or additional weight loss. The same key theoretical constructs were reinforced for the personal contact and interactive technology group. Change in weight was the outcome of interest and was measured from the start of Phase 2 to the end of the study (30 months). Results showed those randomized into the personal contact group regained significantly less weight than participants in the self-directed and interactive technology groups. Furthermore, the effect was seen across all subgroups regardless of gender, ethnicity or age, suggesting this may be a feasible public health
approach. Despite findings that would support face-to-face interventions over web-based interventions, the authors suggest prioritizing interactive technology approaches based on their cost effectiveness and potential for wide dissemination. They also acknowledge the need for further research that might help identify predictors of successful weight loss maintenance.

Consistent and continual use of technology is another component of web-based intervention approaches that has been examined. Polzien, Jakicic, Tate and Otto (2007) examined short-term weight loss in three groups of participants who used a technology-based intervention continuously, intermittently or received traditional face-to-face counseling during a 12-week behavioral intervention. Technology arm participants used an interfaced device that measured energy expenditure and logged dietary intake on an internet site. All participants engaged in seven individualized counseling sessions during the 12 week period. The sessions were based on constructs of social cognitive theory, emphasizing exercise and eating behaviors associated with successful weight loss. Completion rates were similar across the groups (88%) with younger participants more likely to be non-completers. Results showed a greater weight loss trend among those that used the continuous approach versus the intermittent approach or the face-to-face approach. Finding face-to-face counseling the least effective, the investigators recommend further study of technology-based interventions and identification of those who may benefit most from such an approach.
Theoretical Considerations

Psychosocial variables that attempt to explain behaviors are found in most health behavior models. For weight management interventions, these variables are of particular interest as they occur at the interpersonal, intra-personal and ecological levels, and are modeled in a variety of ways. The integration of behavioral theory into health improvement interventions like weight loss is still lacking (Palmeira, et al., 2007). Furthermore, there is scarce information available regarding behaviors that involve the use of multi-dimensional interactive technology (self-monitoring tools combined with online social support) to improve health. Understanding key components of old and new theories will be of great utility in countering the health issues of the modern world, especially weight management.

Self-Regulation

Self-regulatory behaviors are focus areas in many weight loss interventions. Weighing oneself regularly is an example of a strategy that allows an individual to regulate behavior based on the feedback of the scale akin to using insulin to regulate blood glucose levels. The Study to Prevent Regain (STOP Regain) focused on maintenance of weight loss and included participants who had lost at least 10% of body weight in the previous 2 years (Wing, Tate, Gorin, Raynor, & Fava, 2006). The 18-month intervention randomized participants into a control group, a face-to-face group, or an internet group and focused on self-regulatory skills such as daily weighing. Weight regain was lowest in the face-to-face group, followed by the internet group, followed by the control group. The researchers note a limitation of the study in failing to find
differences in self-reported diet or activity measures. However, the emphasis on regular self-weighing—an important self-monitoring skill—appeared to be an effective weight regain strategy in and of itself. In a follow-up paper, Wing and colleagues (2007) reported no adverse effects of daily weighing in the successful weight losers, finding that more frequent weighing was association with more eating restraint.

**Social Cognitive Theory**

Social learning is the cornerstone of Bandura’s (1986) Social Cognitive Theory (SCT), where human behavior is a function of a triangular, reciprocal learning model. The basic premise is that personal factors, the environment and behavior continually interact. In this dynamic, people learn not only through their own experiences, but also by observing the actions of others and the results of those actions. In other words, behavior follows a cognitive, decision-making pathway. Constructs of the theory are observational learning, reinforcement, self-control, and self-efficacy. These constructs provide an ideal framework for behaviors that involve technology enabled health management, as they often involve setting small, incremental and achievable goals, using formalized behavioral contracting, and monitoring and reinforcement, including self-monitoring.

Several recent studies have used SCT as the basis for weight loss and or weight gain prevention interventions. Smith Anderson-Bill, Winett and Wojcik (2011) examined the personal and behavioral characteristics of web users enrolled in the online based Guide to Health intervention. Of the 731 participants who completed the 18-month trial, most were well-educated, non-Hispanic white women who were overweight and
sedentary. The study found participants who lacked self-regulation behaviors, perceived low social support and had lower self-efficacy scores did not demonstrate healthy behavior changes with regard to diet and physical activity. These results suggest that perceived social support, self-regulatory behaviors and levels of self-efficacy were positively correlated with healthy behavior changes. These findings are important for numerous reasons. First, a target demographic was identified. Secondly, the sample size indicates the practicality and efficacy of using an entirely internet-based approach.

Rejeski, Mihalko, Ambrosius, Bearon and McClelland (2011) conducted a 6-month intervention on older, obese adults to examine associations between self-regulatory, self-efficacy behaviors and weight loss. Two hundred eighty eight adults were randomized into a physical activity only group, a weight loss plus physical activity, or a successful aging health education program. Using the weight efficacy lifestyle questionnaire as a self-efficacy measure, the researchers observed an increase in self-efficacy in the weight loss and physical activity group only, and the change in self-efficacy mediated the effects of the intervention on weight loss. It should be noted that this was a group mediated intervention and was not web-supported. Technology was employed in the form of an accelerometer that was used to assess functional capacity in all participants.

Higher self-efficacy scores have been associated with improved weight loss outcomes in overweight/obese postmenopausal women (Shin, Shin, Liu, Dutton, Abood, & Ilich, 2011), another potential target group. In a 6-month weight loss intervention (n=90), women who scored higher in self-efficacy were able to lose more weight and
regulate eating as compared to those that had low self-efficacy scores. This was an in-person intervention, so the conclusions cannot be generalized to all intervention designs. However, the findings are compelling and reinforce the importance of promoting self-efficacy in interventions that target older, at risk women.

*Autonomy and Self-Determination*

A focus on competence, akin to the SCT’s self-efficacy construct, is a central theme in Self-Determination Theory (SDT). This theory explains the nature of human motivation, based on three basic needs; the need for autonomy, the need for competence, and the need for relatedness (Deci & Ryan, 2000). These three constructs provide the framework for understanding behaviors involved in online social networking, where activities such as “friending” are generally intrinsically driven. Unlike other behavioral theories, the SDT has a qualitative nature to it, considering human personality and emotions as underpinnings for behavior. The theory posits that intrinsic motivations are pleasant, enjoyable, while extrinsic motivations are more outcome orientation, or outward. This is the key characteristic of the theory, where motivation can come intrinsically from “wanting to” rather than extrinsically from “having to” do something (Teixeira, Carraça, Markland, Silva, & Ryan, 2012). For long term weight loss to be sustained, the theory authors suggest building intrinsic motivation skills (Ryan & Deci, 2000). Online social networking may be an effective linkage for intrinsically motivated health behaviors among support partners.
Social Support

Behavioral research has focused on social support, demonstrating strong and reciprocal relationships among social support, health and health behaviors (Verheijden, Bakx, van Weel, Koelen, & van Staveren, 2005; Berkman, Glass, Brissette, & Seeman, 2000). With regard to weight loss, social support has been a longstanding research interest. To date, several studies have shown social support to have a positive influence on weight loss efforts. Foundational work by Black, Gleser & Kooyers (1990) found that involving friends in weight loss efforts improved weight loss outcomes, and simply involving support partners in behavioral weight control treatment was an effective strategy for weight loss as well as weight loss maintenance.

Subsequent research has found that weight loss was not necessarily dependent on the number of support partners but rather the successful weight loss of the partner (Gorin, Sherwood, Jeffrey, Phelan, Tate, & Wing, 2005). This study found that participants with at least one successful partner (with weight loss equivalent to or greater than 10% at 6 months) lost significantly more weight in the short and longer term than those with no successful partners.

Kumanyaki et al (2009) examined the cultural relevancy of social support in African Americans who participated in a 2-year weight loss trial either individually (no support person assignment) or in assignment with one or more family members or friends. The results showed no significant individual effect on weight change associated with level of support assignment. Rather, like Gorin, Sherwood, Jeffrey, Phelan, Tate
and Wing’s (2005) study, individual weight loss was associated with *actual* rather than *assigned* partner weight loss.

Similarly, Kiernan et al. (2012) assessed the psychometric properties of group support in women that participated in a 6-month group-based weight loss intervention. The study found that overweight women who reported never experiencing support from family, were the least likely to lose significant weight (5% or more of initial weight), women who experienced frequent friend and family support were more likely to lose weight, and women who never experienced friend support were the most likely to lose weight. The researchers postulate this seemingly contradictory finding was due to the fact that the group-based design provided support that was lacking from friendships.

Several weight loss study designs have shown promising results using a team-based approach to socially connect subjects who have common health-related goals. Overweight adults who participated in an online 12-week program (Gokee Larose, Leahey, Weinberg, Kumar, & Wing, 2012) demonstrated 5% or more weight loss when they were on a team, leading the researchers to conclude that social influence could lead to clinically significant weight loss. A 2007 study at the University of Michigan involved over 7000 students and faculty that enrolled in an online health improvement program. Active U was an 8-week intervention that focused on the promotion of physical activity during the harsh winter months. Investigators found that participants who were part of a team were much more likely to meet physical activity and weight loss/maintenance goals than individual participants (Buis, et al., 2009).
Social support has long been associated with improved health (Uchino, 2004; Cohen & Syme, 1985; Berkman, 1995) but the mechanisms of technology-facilitated social support in scientifically designed interventions have not been well-studied to date. With more technology-oriented research efforts including a social support component, this area warrants further investigation.

**Concluding Statements**

Combining interactive technology and social support appears to have great potential as an alternate and effective strategy for weight loss, weight loss maintenance, and obesity prevention, as seen in the review of current literature. Elements of technology are already in use for health and fitness tracking on an individual level and are increasingly being used in weight loss and health improvement interventions. Clinical applications have been tested and are gaining acceptance as a practical approach to lifestyle management. Technology continues to advance at a rapid pace, and more and more behavioral scientists are eager to leverage the convenience and reach of integrated web-based approaches.

Current and on-going research using technology approaches has strengthened the rationale for a new breed of interventions that use scientifically defensible strategies designed to improve health and reduce obesity. Technology-enabled interventions that incorporate behavioral constructs of skill-building, self-regulation, self-efficacy, and social support may be the key to improved outcomes and eventual population health improvement. Interventions that combine interactive technology and social support can be tailored to target populations—employees, children, at risk individuals, minorities.
This research effort intends to inform future design and implementation of public health interventions, with particular emphasis on weight reduction interventions for targeted populations. If the past is prelude to the future, we can expect to see continued advancements in technology which are likely to include even more options and applications for health management. Understanding which features work for which outcomes and for whom will be invaluable in the quest for sustainable behavior changes. The challenge will be to keep pace with and harness technology as a standard means of improving population health. There may be no more effective way to halt the advancement of one of the most costly epidemics of modern times.
Chapter 3

Methods

Overview and Rationale

The present work is an exploratory analyses of potential factors associated with technology-enabled weight loss among adult healthcare workers who completed the experimental arm of the iWell Clinical Trial. This was a collaborative study done by SK Telecom Americas, Inc., and PeaceHealth Laboratories. iWell was a 6-month randomized controlled trial conducted in a healthcare setting located in Springfield, Oregon. This trial compared technology-enabled (experimental group) participants to self-directed (control group) participants and determined that weight loss and physical activity patterns were significantly greater among participants in the technology-enabled group (Greene, Sacks, Piniewski, Kil, & Hahn, 2012). Major findings indicated that the technology-enabled experimental group lost more weight and increased their physical activity more as compared to the self-directed control group. Those in the technology-enabled group increased walking time 164% over the 6-month trial compared to a 47% increase in the self-directed group. They lost 5.2 pounds compared to 1.6 pounds, respectively. In addition, sending messages on the online social network appeared to contribute to weight loss efforts and increased physical activity. However, investigators found no differences in cardiovascular or metabolic risk markers between or among the groups from baseline to 6 months.

Although the 6-month iWell study provided important information about the short-term impact of technology on weight loss interventions, it did not draw conclusions
about characteristics of technology users, extent of technology use, specific features of technology that were predictive of success, or of longer term effectiveness.

The primary goal of the present research effort is to identify key factors that contributed to weight loss and weight loss maintenance among the technology-enabled participants who participated in the iWell weight loss intervention. Were there some inherent individual factors that contributed to utilization and adherence to technology-related program components? Could these factors be modified in subsequent interventions to increase the nature and extent of involvement in such programs? Were there factors that served as unique barriers to involvement? To assess these questions, existing data from technology-enabled participants who completed the iWell Clinical Trial were used for analyses related to short-term outcomes (n=168). To examine longer term outcomes, data from a subsample of the 168 technology-enabled participants one year after study completion (n=48) were used. The same variables examined from the 6-month trial were examined from baseline to one year post-intervention. In addition, at one year post-intervention, self-reported current health status, physical activity level, self-monitoring frequency and online social network data were examined to investigate behavioral and perceptual factors of the subsample that may have influenced longer term outcomes.

**Research Questions and Hypotheses**

Based on unanswered questions involving the technology-enabled participants who completed the 6-month trial, the following primary and secondary research questions and hypotheses form the basis for the present study:
1. Were there differences in weight loss in the technology-enabled participants as measured by % BMI change based on age, gender, disease burden (as indicated by baseline BMI, insulin resistance, HbA1c levels) and use of online social networking (OSN) from baseline to 6 months?

   **Hypothesis:** Differences in weight loss in technology-enabled participants will be predicted by age, gender, disease burden and overall utilization of the online social network.

2. Was technology feature utilization (activity uploaded, weight uploads, and OSN use) associated with weight loss as measured by % BMI change from enrollment baseline (pre-test) to 6 months (post-test)?

   **Hypothesis:** Differences in weight loss will be predicted by nature and extent of selected technology feature utilization.

3. Did the technology-enabled participants demonstrate maintenance of weight loss as measured between baseline and one year post-intervention?

   **Hypothesis:** Weight loss in technology-enabled participants was maintained from baseline to one year post-intervention.

4. For technology-enabled participants that completed the initial 6-month study, did weight loss maintenance at one year post-intervention differ according to age, gender, perceptions of benefit, current health status, activity levels and self-monitoring of weight?
Hypothesis: Weight loss maintenance at one year post-intervention will be predicted by age, gender, perceptions of benefit, current health status, activity levels, and self-monitoring.

Secondary Research Question:

5. At one year post-intervention, was there evidence of reduced disease risk among technology-enabled participants as seen by changes in cardiovascular and metabolic risk markers and were certain variables predictive of this?

Hypothesis: Risk factors for cardiovascular and metabolic disease differed from baseline to one year post-intervention, and varied by age, gender, perceptions of health, current self-monitoring and physical activity levels.

**Study Population**

Data for this research were collected as part of the iWell Trial, a randomized clinical trial of adult healthcare employees who volunteered for a weight loss and health improvement program. Data were collected from October 2010 to December 2012 using in-person measurements, website data mining, and self-administered surveys to gather information on clinical markers of cardiovascular and metabolic diseases, physical activity patterns, and weight. Inclusion criteria for participation in the iWell study are listed below:
Inclusion Criteria:
- Age: 18 years or older
- Overweight or obese men and women (BMI greater than 24)
- Concerned about weight/health (and motivated to lose weight)
- Stable medications for past 3 months
- Willing/able to use web-based services
- Willingness not to use weight loss medications for the duration of the trial
- Able and willing to give informed consent and participate in the interventions
- Willing to attend three sessions and visits
- Willingness to be randomized to intervention or control group

Approximately 5,000 employees in the PeaceHealth Oregon Region healthcare system were made aware of the study through recruitment materials that were distributed through employee e-mails, newsletters, posters and flyers posted in common work and break areas. The target population was overweight adults (BMI greater than 24) who were not currently undergoing bariatric treatment.

A total of 513 people enrolled in the study, with 500 meeting eligibility. Enrollment sessions were held between October 2010 and March 2011 to achieve the desired sample size. For sample size, the investigators selected 250 to achieve 80% power (alpha 0.05) for detecting differences between two population means, using a two-side z-test and assuming equal variance in the experimental and control groups.

At enrollment sessions, participants provided informed consent and were randomized into either a control (self-directed) group (n=250) or an experimental (technology-enabled) group (n=250). Retention was similar for both groups (66%) with 165 self-directed and 168 technology-enabled participants completing the 6-month trial. All participants underwent biometric and biomarker assessments at baseline, 3 months and 6 months. Risk markers for cardiovascular and metabolic disease (including weight,
fractionated lipids, blood glucose and HbA1c) were collected at these intervals, using standard lab procedures and trained lab technicians. Copies of the assessments and interpretation of results were given to the participants after each assessment. Participants with critically abnormal values were referred to a primary care provider for follow up.

The control subjects were given usual care educational materials and resources focused on a self-directed program of recommended levels of daily physical activity and caloric restriction. The experimental participants were given wireless tracking instruments including a scale and an accelerometer that measured free living activities and exercise intensity. These instruments interfaced with a web-based software package that downloaded to a personal computer and was linked to the iWell website. Participants were asked to wear the accelerometer daily and were instructed on how to perform data uploads from the activity tracker and scale. Participants received training on how to personalize a homepage (the iWell “dashboard”), identify goals, and view and monitor activity and weight progress throughout the study period. Biomarker and biometric assessments were uploaded to individual dashboards by the study investigators, after each assessment. Values were color-coded to indicate risk level. For example, green indicated “low risk,” yellow indicated “moderate risk,” and red indicated “high risk.” Participants also received instruction on how to use the private, designated online social network to communicate with other subjects. Use of the technology features and how they may have contributed to the intervention effectiveness is a key focus of this secondary analysis. All self-monitoring activities, data uploads and online social network use was tracked by the study investigators throughout the 6-month trial.
To investigate weight loss maintenance and other indicators of health improvement post-intervention, an addendum was submitted to the IRB offices of PeaceHealth and Oregon State University IRB’s requesting an additional assessment one year post-intervention. This post-intervention assessment was designed to examine longer term effects of the intervention, and factors associated with longer term outcomes. The sample for the one year post-intervention collection was limited to technology-enabled participants who had completed all assessments for the 6-month trial and had data available to indicate use of technology features such as online social networking, physical activity and weight uploads. A total of 168 technology-enabled participants completed the 6-month intervention and were eligible for the follow up study. These participants were contacted using the same email addresses used during the 6-month study. Four invitations containing instructions for participation and consent forms were sent to participants over the course of 2 months. Collection of biomarkers and biometrics replicated procedures used in the 6-month study, including the use of the same facilities and personnel. Participants had 10 weeks to complete the assessment which was offered free of charge. A total of 69 participants responded to the invitation, equating to a 41% response rate. Of the 69 respondents, a total of 48 participants completed the one year follow up assessment. Repeated measures were used to examine the same variables assessed at baseline, 3 months and 6 months, using the same personnel and laboratory procedures. In addition, self-reported current health status, physical activity level, weight monitoring frequency and current online social network use were examined to provide additional qualitative information about the participants in the subsample.
Data Collection

De-identified data for technology-enabled participants were obtained from the investigators of the iWell study after obtaining approval from both Oregon State University and PeaceHealth IRB committees. For secondary analysis purposes, a data set was created from the 6-month trial and the one year post-intervention assessment and included variables of gender, age, age group, total activity uploaded (in mileage), height, weight, and baseline, 6-month and one year post-intervention biomarkers and biometrics (body mass index, HbA1c, fasting LDL, HDL, blood glucose and triglycerides). Disease burden was determined by baseline risk status for cardiovascular and metabolic disease (BMI, LDL, insulin resistance or triglyceride/HDL, and HbA1c). Total number of weight uploads was tabulated. Activity uploaded was recorded as total mileage uploaded from the accelerometer from baseline to 6-months. Online social network (OSN) activity was measured by the sum of number of friend requests, public posts and public comments made by each participant. Use of these three OSN features--friend requests, public posts, and public comments--was documented by the monitoring software. Totals for each were used for the data set. Weight change is indicated by percent change in BMI, as calculated from baseline to 6-month, 6-month to one year post-intervention, and baseline to one year post-intervention. Gender was either female or male as self-reported, and age was as of January 1, 2011. Age was age at time of enrollment. Time points for the variables used in the analyses are baseline, 6-month, and one-year post-intervention. Data regarding perceptions of benefit, current health status, and current
monitoring and physical activity habits were collected at one year post-intervention by self-report and rank order scale responses (see examples below).

- **In general, would you say your health is:**
  
  excellent  very good  good  fair  poor

- **How often do you weigh yourself?**

  Daily  weekly  monthly  not regularly

- **Participating in the iWell Study improved my health.**

  Strongly Disagree  Disagree  Neutral  Agree  Strongly Agree

- **Being able to track my weight over the course of the study had a positive impact on my health.**

  Strongly Disagree  Disagree  Neutral  Agree  Strongly Agree

Data usage plans and study procedures were approved by the Oregon State and PeaceHealth IRB’s.

The following aims involve secondary analyses of technology-enabled participants in the iWell study dataset. The main variables of interest include the following: weight change, age, gender, disease burden (as indicated by baseline BMI, insulin resistance, and HbA1c and levels), technology feature use (activity uploaded, weight uploads, online social network activity), perceived health status, current health habits, and perceived benefit from participation in the study.
Specific Aims

Specific Aim 1: Determine predictors of weight loss in overweight and obese healthcare workers who used multi-component interactive technology and online social networking in a 6-month weight loss intervention.

The purpose of this aim is to determine factors that were associated with participants who were most successful losing weight using the technology-enabled approach, as measured from baseline to 6-month study completion. Were certain characteristics such as age, gender and disease burden predictive of weight loss? To what degree was utilization of the technology features and the OSN associated with weight loss?

Dependent Variable: Weight Loss (% BMI change)

In overweight persons, weight loss of 3% has been shown to favorably modify risk factors for cardiovascular disease (Blackburn, 1995; Donnelly, Blair, Jakicic, Manore, Rankin, & Smith, 2009; National Institutes of Health Consensus Development Panel on the Health Implications of Obesity, 1985). In this analysis, weight change is calculated as a percentage change from baseline BMI to 6-month BMI. In this analysis, a 3% decrease was considered to be consistent with health improvement.

Statistical Analyses

Measures of central tendency provide descriptive statistics of the variable of interest in study population. These data are expressed as means, medians, standard deviations and ranges. Single and multiple variable linear regression analyses are used to explore predictive models. The outcome of interest (dependent variable) is weight
loss, calculated as percent change in BMI from baseline to 6 months. Independent variables include age, gender cardiovascular and metabolic disease risk markers (LDL, insulin resistance, and HbA1c levels, and use of the online social network. Weight loss will also be analyzed according to technology feature use (activity uploaded, weight uploads and use of the online social network). Comparisons between the variables of gender and these technology features will be made with regard to weight change outcomes. Single and multiple variable regression models will allow further examination of the predictive strength of technology feature variables. Stata for Windows, version 10.1 (College Station, Texas) is used for data analyses.

Specific Aim 2: Determine longer term effectiveness of an interactive technology and online social networking intervention at one year post-intervention and examine variables associated with maintained weight loss and health improvement.

This aim is designed to determine the longer term outcomes for technology-enabled participants. Specifically, were health improvements such as weight loss maintained from baseline to one year post-intervention? Were changes in biomarkers for cardiovascular and metabolic diseases different from baseline to one year post-intervention? Were personal characteristics (age, gender), current activity and self-weighing habits, and perceptions of benefit associated with longer-term maintenance and risk reduction as indicated by repeated biomarker and biometric measures assessed one year post-intervention?

Dependent Variables: Weight Loss (% BMI Change) and Change in Cardiovascular and Metabolic Risk Markers
Weight will be compared from baseline to one-year post-intervention to determine whether weight loss was maintained one year post study completion. Weight change will be reported as percent change in BMI from baseline to one year post-intervention. Cardiovascular and metabolic risk markers will be compared from baseline to one year post-intervention to determine changes reflective of risk reduction. Changes in these markers will be examined proportionally for the subsample of technology-enabled participants.

Statistical Analyses

A power analysis was conducted with the goal of detecting a mean difference in BMI from baseline to one year post study completion for the technology-enabled group, using PS Power Sampling, version 3.0, January, 2009 (Dupont & Plummer, 1990). The effect size considered to be of practical importance is a BMI change of 3% (SD=1.5) from baseline to one year post-intervention and was estimated based on a sample size of 48 (alpha .05). Paired t tests are used to examine differences in weight loss and cardiovascular and metabolic risk markers (LDL, triglycerides, HDL, insulin resistance, fasting blood glucose, and HbA1c) from baseline to one year. Single and multiple variable linear regression are used to examine whether age or gender were predictive of weight loss maintenance. Frequency tabulations are used to describe overall responses to health status, self-monitoring, current activity levels, current OSN use, and perceptions of benefit related to study participation. Spearman’s rank order correlation will be used to test for relationships between weight loss maintenance and these responses. To address differences in risk markers at one year post-intervention, McNemar’s test of proportions
is used, comparing proportion of “normals” for risk markers (LDL, insulin resistance, HbA1c and blood glucose) at baseline and one year. Single and multiple linear regression analyses are used to examine whether changes in risk markers were associated with age, gender, perceptions of health, current self-monitoring and activity habits. Stata for Windows, version 10.1 (College Station, Texas) will be used for data analyses.
Chapter 4

Results

Several research hypotheses were tested to determine whether certain variables were predictive of short and longer term weight loss outcomes in overweight adult healthcare workers who used interactive technology to improve health and lose weight in a 6-month clinical, as measured at the end of the intervention and one year post-intervention follow up. Four primary hypotheses guide the analyses:

1. Differences in weight loss in technology-enabled participants from baseline to the end of the intervention could be predicted by age, gender, disease burden and overall utilization of the online social network;

2. Differences in weight loss from baseline to the end of the intervention could be predicted by nature and extent of selected technology feature utilization;

3. Weight loss in technology-enabled participants was maintained from baseline to one year post-intervention;

4. Weight loss maintenance at one year post-intervention could be predicted by age, gender, perceptions of benefit, current health status, activity levels, and self-monitoring.

A secondary hypothesis examined differences in cardiovascular and metabolic risk factors from baseline to one year post-intervention, and factors associated with those differences:
1. Risk factors for cardiovascular and metabolic disease differed from baseline to one year post-intervention, and varied by age, gender, perceptions of health, current self-monitoring and physical activity levels.

Results will be provided in the following sections: Section 1 presents findings from the 6-month trial and addresses the first two hypotheses regarding weight loss outcomes as measured from baseline to the end of the intervention. Section 2 presents findings from the one year post-intervention analyses and addresses hypotheses 3 and 4 as well as the secondary hypothesis.

Section 1

Sample Characteristics of Participants in the 6-month iWell Clinical Trial

Participants in the iWell Clinical Trial were adult healthcare workers in Lane County, Oregon, who self-identified as wishing to improve health and lose weight, and volunteered to participate in the on-site study. A total of 500 participants were enrolled in the trial and were randomized either into a control (self-directed) group or an experimental (technology-enabled) group. The primary aim of the iWell intervention was to compare weight loss and physical activity outcomes among the two groups. The majority of participants in the study were females (79%), 50 years or older (60%). Retention was similar for both groups with 66% (165 control and 168 experimental participants) completing baseline and 6-month assessments. Table 4.1 presents pre- and post-intervention values of both experimental and control group participants in the 6-month study. At baseline, the two groups were not significantly different in terms of age, gender, or cardiovascular and metabolic disease markers (LDL cholesterol, insulin
resistance ratio, HbA1c). In the technology group and the self-directed group, the average female BMI was slightly higher than the average male BMI (30.9 kg/m² and 31.4 kg/m² compared to 29.8 kg/m² and 30.2 kg/m²) at baseline. At baseline, self-directed participants had essentially the same BMI as the technology group (31.2 kg/m² compared to 30.6 kg/m²). The technology group was slightly older than the self-directed group (49.8 years versus 48.8 years). On average, males in the technology group had higher clinical risk markers for diabetes compared to self-directed participants (insulin resistance ratio of 2.7 compared to 2.1 and HbA1c of 5.8% compared to 5.4%).

Table 4.1: Mean values of Clinical Indicators at Baseline and 6 Months, for Experimental (Technology-Enabled) and Control (Self-Directed) Participants

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Males</td>
<td>Females</td>
<td>All</td>
<td>Males</td>
<td>Females</td>
<td>All</td>
</tr>
<tr>
<td>BMI (kg/m²)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exp</td>
<td>29.8</td>
<td>30.9</td>
<td>30.6</td>
<td>29</td>
<td>30.1</td>
<td>29.8</td>
</tr>
<tr>
<td>Control</td>
<td>30.2</td>
<td>31.4</td>
<td>31.2</td>
<td>29.8</td>
<td>31.2</td>
<td>30.9</td>
</tr>
<tr>
<td>LDL (mg/dl)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exp</td>
<td>115.1</td>
<td>115.6</td>
<td>115.5</td>
<td>115.1</td>
<td>116.9</td>
<td>115.7</td>
</tr>
<tr>
<td>Control</td>
<td>127.2</td>
<td>114.6</td>
<td>116.9</td>
<td>128.7</td>
<td>120.5</td>
<td>122</td>
</tr>
<tr>
<td>Insulin Resistance*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exp</td>
<td>2.7</td>
<td>2.0</td>
<td>2.5</td>
<td>2.9</td>
<td>2.2</td>
<td>2.4</td>
</tr>
<tr>
<td>Control</td>
<td>2.1</td>
<td>2.1</td>
<td>2.1</td>
<td>3.1</td>
<td>2.2</td>
<td>2.4</td>
</tr>
<tr>
<td>HbA1c (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exp</td>
<td>5.8</td>
<td>5.5</td>
<td>5.6</td>
<td>5.7</td>
<td>5.5</td>
<td>5.6</td>
</tr>
<tr>
<td>Control</td>
<td>5.4</td>
<td>5.4</td>
<td>5.4</td>
<td>5.4</td>
<td>5.5</td>
<td>5.5</td>
</tr>
</tbody>
</table>

Note: Exp=Technology-enabled participants, Control=Self-directed participants
Males: Exp n=37, Control n=30. Females: Exp n=131, Control n=135.
*Insulin Resistance=Triglycerides/HDL

As previously reported (Greene, Sacks, Piniewski, Kil, & Hahn, 2012) weight loss was significantly greater in the technology-enabled group as compared to the self-
directed group at 6 months. Within the intervention and self-directed groups, biomarkers for cardiovascular and metabolic disease (LDL, insulin resistance, HbA1c) were not significantly different as measured between baseline and end of study.

Research Hypothesis 1

Weight loss in technology-enabled participants differed according to age, gender, disease burden and online social network use as measured from baseline to 6-month study completion.

Single variable regression was used to model the relationship between weight loss as the dependent variable and each explanatory variable (age, gender, disease burden and total use of the OSN). The results of the analyses are summarized in Table 4.2 and Figure 1. This table presents the results of the regression model for single predictors in the sample of intervention participants in the 6-month trial. Weight loss is reported as percent change in BMI according to each predictor. The formula used for the response variable is:

\[
100 \left( \frac{\text{BMI at 6 months} - \text{BMI at baseline}}{\text{BMI at baseline}} \right).
\]

Demographic characteristics of age and gender were not found to be significant predictors of weight loss (p-values of 0.08 and 0.75, respectively). Disease burden as indicated by risk status (baseline BMI, insulin resistance ratio and HbA1c) was also not predictive of weight loss (p-values of 0.76, 0.92 and 0.62) suggesting risk status was not associated with subsequent weight loss. Online social network (OSN) use was determined by the 6-month total sum of friend requests, posts, and comments. In the
single variable model, total OSN use was not found to be a significant predictor of weight loss. According to this analysis, weight loss did not differ significantly according to participant age, gender, cardiovascular or metabolic disease burden, or use the OSN.

Scatterplots (Figure 1) display an absence of linear correlation between single predictors and weight loss, with no obvious slope indicating a negative % BMI change.

Table 4.2: Single Variable Regression Analysis—Predictors of Weight Loss in 6-Month Intervention Participants

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Coefficient (SE)</th>
<th>p-Value</th>
<th>R-Squared</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>-.05 (.03)</td>
<td>0.08</td>
<td>0.0181</td>
<td>-.11, .01</td>
</tr>
<tr>
<td>Gender</td>
<td>.24 (.77)</td>
<td>0.75</td>
<td>0.0006</td>
<td>-1.29, 1.77</td>
</tr>
<tr>
<td>Baseline BMI</td>
<td>.02 (.06)</td>
<td>0.76</td>
<td>0.0006</td>
<td>-.11, .15</td>
</tr>
<tr>
<td>Baseline IRR</td>
<td>-.02 (.24)</td>
<td>0.92</td>
<td>0.0001</td>
<td>-.49, .44</td>
</tr>
<tr>
<td>Baseline HbA1c</td>
<td>-.19 (.38)</td>
<td>0.62</td>
<td>0.0015</td>
<td>-.94, .56</td>
</tr>
<tr>
<td>Total OSN Use</td>
<td>-.02 (.02)</td>
<td>0.32</td>
<td>0.0061</td>
<td>-.05, .02</td>
</tr>
</tbody>
</table>

N=168 (males=37, females=131)
Multiple variable linear regression analysis was used to simultaneously test and model multiple predictor variables. Table 4.3 presents the results of this model combining the predictors of age, gender, baseline disease burden and use of the OSN. In this multivariate model, none of the variables were found to be significant predictors of weight loss. Demographic characteristics of age and gender were not predictive of weight loss. Disease burden as indicated by risk markers of baseline BMI, insulin resistance and HbA1c was also not predictive of weight loss at 6-months. No significant association was found between OSN use (total 6-month count of friend requests, posts and comments) and weight loss at 6 months. Although weight loss (-2.6% BMI change) from baseline to 6-months occurred in the technology-enabled participants, these findings
indicate no significant association between personal characteristics, baseline disease burden, or online social network engagement and subsequent weight loss at study completion.

Table 4.3: Multiple Variable Regression Model—Predictors of Weight Loss in 6-Month Intervention Participants

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Coefficient (SE)</th>
<th>p-Value</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>-0.05 (.03)</td>
<td>0.09</td>
<td>-.11, .01</td>
</tr>
<tr>
<td>Gender</td>
<td>-0.02 (.84)</td>
<td>0.98</td>
<td>-1.64, 1.6</td>
</tr>
<tr>
<td>Baseline BMI (kg/m²)</td>
<td>0.02 (.07)</td>
<td>0.75</td>
<td>-.12, .17</td>
</tr>
<tr>
<td>Baseline IRR</td>
<td>-0.09 (.27)</td>
<td>0.75</td>
<td>-.62, .45</td>
</tr>
<tr>
<td>Baseline HbA1c (%)</td>
<td>-0.12 (.47)</td>
<td>0.80</td>
<td>-1.1, .82</td>
</tr>
<tr>
<td>Total OSN Use</td>
<td>-0.02 (.02)</td>
<td>0.26</td>
<td>-.05, .01</td>
</tr>
</tbody>
</table>

N=168 (males=37, females=131)
IRR=Insulin Resistance Ratio (Triglycerides/HDL)
F test of model significance had F (6, 160)=0.74 and p-value=0.62, Adjusted R-squared=0.01

Research Hypothesis 2

At six months, differences in weight loss will be predicted by nature and extent of selected technology feature utilization.

The majority of the health habits and social data collected during the 6-month trial came from wireless transmittals or direct use of multi-component technology features that were integrated into the intervention design. During enrollment, participants were instructed on how to use the wireless instruments (an accelerometer and scale) and were trained to personalize a homepage and utilize the communication features of the online social network (OSN). After training, participants were encouraged to use the devices and engage in OSN activities on a daily basis.
Table 4.4 summarizes average technology feature use by the technology-enabled participants as a group and by gender during the 6-month study. Activity uploaded represents total activity (in mileage) uploaded from the accelerometer to the iWell portal from baseline to 6 months. Weight uploads represent the number of times a participant weighed and transmitted weight data to the website portal during the 6-month study period. Total OSN use was the sum of friend requests, posts and comments made throughout the 6-month study.

During the 6-month study period, the average total distance uploaded was 519 miles. The average number of times a participant transmitted weight was 39. On average, participants friended, posted or commented on the OSN 11.2 times throughout the 6-month study period. Mean values indicate that males averaged more uploaded activity than females and weighed themselves (on average) more times than females throughout the study period. Average use of the OSN was similar for males and females, with females using the OSN slightly more than men (11.4 times versus 10.7 times) during the study period.

Table 4.4: Average Use of Technology Features by Gender

<table>
<thead>
<tr>
<th>Technology Feature</th>
<th>Males n=37</th>
<th>Females n=131</th>
<th>Total n=168</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activity Uploaded (miles)</td>
<td>755 (530)</td>
<td>453 (281)</td>
<td>519 (371)</td>
</tr>
<tr>
<td>Weight Uploads (count)</td>
<td>48 (51)</td>
<td>35 (40)</td>
<td>39 (43)</td>
</tr>
<tr>
<td>Total OSN Use</td>
<td>10.7 (19.3)</td>
<td>11.4 (21.1)</td>
<td>11.2 (20.7)</td>
</tr>
</tbody>
</table>

Values reported as means (SD)

To test the relationship between use of the technology features and weight loss, single variable linear regression modeling was used. Table 4.5 presents the results of the technology feature utilization linear regression analyses for the group as well as
according to gender. The analyses found activity uploaded from the accelerometer to be a statistically significant predictor of weight loss as indicated by percent change in BMI (p<0.001, estimated percent BMI change of -.003) as was total number of weight uploads (p<0.001, estimated percent BMI change of -.03). Online social network (OSN) use was another technology feature hypothesized to be associated with weight loss and was consequently included in the regression analyses pertaining to technology use. This analysis of activity uploaded and weight uploads revealed significant differences in weight loss according to gender. Activity uploaded and weight uploads were statistically significant predictors of weight loss for both males and females (p<0.05) for both indicating statistically significant associations between the use of these features and subsequent weight loss. Total use of the OSN was greater for females than males, but was associated with weight loss only for males (p-value=0.001). This finding suggests a correlation between males using the OSN and subsequent weight loss.

| Table 4.5: Single Regression Analysis--Technology Feature Use and Weight Loss |
|-------------------------------------------------|-----------------|-----------------|-----------------|-----------------|
| Technology Feature                              | Coefficient (SE) | p-Value          | R-squared       | 95% CI          |
| Activity Uploaded                               | -.003 (.001)     | 0.001**          | 0.07            | -.005, -.002    |
| Weight Uploads                                  | -.03 (.01)       | 0.000***         | 0.07            | -.04, -.01      |
| Total OSN Use                                   | -.02 (.02)       | 0.316            | 0.0061          | -.05, .02       |

**Males**
- Activity Uploaded: -.004 (.001)  p-Value = 0.004**
- Weight Uploads: -.04 (.01)  p-Value = 0.005**
- Total OSN Use: -.12 (.03)  p-Value = 0.000***

**Females**
- Activity Uploaded: -.003 (.001)  p-Value = 0.03*
- Weight Upload: -.02 (.01)  p-Value = 0.02*
- Total OSN Use: .01 (.02)  p-Value = 0.644

Males (n=37) Females (n=131)
*p<0.05, **p<0.01, ***p<0.001
Multiple regression analysis was used to test and model the combined technology feature variables of interest. The results of the analysis are presented in Table 4.6.

Similar to the single variable models, the multiple regression model showed activity and weight uploads (from the wireless instruments) to be associated with weight loss (both p-values<0.05).

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Coefficient (SE)</th>
<th>p-Value</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activity Uploaded</td>
<td>-.002 (.0009)</td>
<td>0.021*</td>
<td>-.004, -.0004</td>
</tr>
<tr>
<td>Weight Uploads</td>
<td>-.02 (.01)</td>
<td>0.016*</td>
<td>-.04, -.004</td>
</tr>
<tr>
<td>Total OSN use</td>
<td>.02 (.02)</td>
<td>.334</td>
<td>-.02, .05</td>
</tr>
</tbody>
</table>

F test of model significance had F(3,164)=6.27 and p-value=0.001, Adjusted R-squared=0.09
*p<0.05, **p<0.01, ***p<0.001

In essence, results of both models suggest that participants who used the technology features were more likely to lose more weight on average between baseline and the end of the 6-month study. For both males and females, more tracking of activity and weight was associated with more weight loss. In addition, for males greater use of the OSN was significantly associated with greater weight loss. The negative slopes of the scatterplots (Figure 2) indicate the association of weight loss and each technology feature (activity uploaded, weight uploads and OSN use). In general, the associations show a trend toward weight loss with more feature utilization, for all three features for males. Similar associations are seen for activity uploaded and weight uploads for females. However, for female OSN use, there is no discernible negative slope to indicate an association with weight loss.
**Figure 2: Technology Feature Use According to Gender**

![Graphs showing technology feature use according to gender.](image)

**Section 2**

**Research Hypothesis 3**

Weight loss maintenance (as indicated by a 3% change in BMI) in technology-enabled participants was demonstrated from baseline to one year post-intervention.

**Power Analysis**

Using PS Power Sampling version 3.0, January, 2009 (Dupont & Plummer, 1990) a power analysis was conducted with the goal of detecting a mean difference in weight loss from baseline to one year post-intervention for the technology-enabled group. The measure for weight loss in this study was percent BMI change, as previous research has found it to be a useful indicator of weight change across time periods, in given populations (Razak, Corsi, & Subramanian, 2013; Cole, Faith, Pietrobelli, & Heo, 2005; Cole, Faith, Pietrobelli, & Heo, 2005; Looker, Knowler, & Hanson, 2001). Using this
measure, the effect size was set to detect weight loss equal to or greater than a -3% BMI change (SD -1.5) from baseline to one year post-intervention. Based on a sample size of 48, a two-sided paired t-test at a significance level of 0.05 has power equal to .99 providing adequate power to minimize the chance of committing a type II error.

**Participant Characteristics**

The sample is a subset of the 168 experimental participants who completed the 6-month intervention, using the interactive technology platform during the study period. The sample of 48 was comprised of 23% males (n=11) and 77% females (n=37). The mean age of the one year post-intervention sample was slightly older (54 years) than the mean age for the 6-month intervention group (50 years), for both males and females. Clinical indicators of the one year post-intervention sample are provided in Table 4.7. Values are provided at baseline, end of 6-month intervention and one year post-intervention. Percent changes in the indicators are presented between the time periods of 1) baseline and end of intervention; 2) end of intervention and one year post-intervention; and 3) baseline and one year post-intervention. At one year post-intervention, mean values for clinical indicators of cardiovascular and metabolic disease risk (BMI, insulin resistance and HbA1c) improved, compared to baseline values. Body mass index showed the most favorable change, with a mean decrease of 4.7% (from baseline to one year post-intervention) for the sample. From baseline to one year post-intervention, mean LDL and fasting blood glucose values actually increased in the sample, though not significantly.
Table 4.7: Mean (Standard Deviation) Clinical Indicators of One Year Post-Intervention Sample of Technology-Enabled Participants

<table>
<thead>
<tr>
<th>Variable</th>
<th>Baseline</th>
<th>6 Mos</th>
<th>1 Yr Post</th>
<th>% Change Baseline to 6 Mos</th>
<th>% Change 6 Mos to 1 Yr Post</th>
<th>% Change Baseline to 1 Yr Post</th>
</tr>
</thead>
<tbody>
<tr>
<td>BMI (kg/m²)</td>
<td>29.7 (4.7)</td>
<td>28.7 (4.6)</td>
<td>28.2 (4.2)</td>
<td>-3.2***</td>
<td>-1.5</td>
<td>-4.7***</td>
</tr>
<tr>
<td>LDL (mg/dl)</td>
<td>118.4 (32)</td>
<td>119.5 (33.9)</td>
<td>127.1 (40.2)</td>
<td>.93</td>
<td>6.3</td>
<td>7.3</td>
</tr>
<tr>
<td>IRR (Trig/HDL)</td>
<td>1.95 (1.08)</td>
<td>2.3 (1.7)</td>
<td>1.8 (1.1)</td>
<td>17.9</td>
<td>-21.7</td>
<td>-7.7</td>
</tr>
<tr>
<td>Fasting BG (mg/dl)</td>
<td>98.2 (14.5)</td>
<td>100.8 (19.6)</td>
<td>100.9 (27.5)</td>
<td>2.6</td>
<td>.1</td>
<td>2.7</td>
</tr>
<tr>
<td>HbA1c (%)</td>
<td>5.7 (.94)</td>
<td>5.7 (.86)</td>
<td>5.6 (.89)</td>
<td>0</td>
<td>-1.75</td>
<td>-1.75</td>
</tr>
</tbody>
</table>

Values reported at means (SD)

Note: IRR=Insulin Resistance Ratio (Trig/HDL)
N=48 (males=11, females=37)
*p<0.05, **p<0.01, ***p<0.001

To determine whether mean weight loss was statistically significant one year post-intervention, paired t-tests were employed in analysis of the sample. With this approach, it was possible to test whether weight loss (the mean percent change in BMI) differed from zero between the time periods of baseline and one year post-intervention. Using this analytic method, estimated mean decrease in BMI percent was 4.7% (p-value=0.001) in the subsample one year post-intervention. As seen in Table 4.7, mean change in BMI from baseline to 6 months in the subsample was found to be significant at -3.2% (p-value<0.0001). The one year follow-up value of -4.7% indicates significant weight loss in the subsample from baseline to one year post-intervention. Weight loss in the sample did not reach significance from 6 months to one year post-intervention (a BMI change of -1.5%, p-value=0.12) but continued to move in a direction that would suggest maintenance of initial weight lost during the intervention. Contrary to numerous weight loss interventions that demonstrate gradual weight regain over time (Witham & Avenell,
2010; Svetkey, et al., 2008; Wing & Phelan, 2005), this finding indicates weight loss was maintained by the subsample participants, one year after the intervention ended.

Research Hypotheses 4

*Weight loss maintenance one year post-intervention could be predicted by age, gender, perceptions of benefit, current health status, activity levels and self-monitoring.*

To determine whether certain characteristics were predictive of weight loss maintenance, single and multiple variable regression analytics were used. The analyses did not find significant associations between age or gender and weight loss maintenance (as measured by percent change in BMI) in the subsample, indicating weak or non-existent associations between age, gender, and weight loss maintenance one year post-intervention (Table 4.8). Multiple regression modeling was used to simultaneously test and model for both age and gender in the one year post-intervention sample. Results of these analyses again show no significant associations between these age or gender and maintenance of weight loss at one year post-intervention, with p-values of 0.15 and 0.66, respectively.

| Table 4.8: Single and Multiple Variable Regression Analyses—Demographic Predictors of Weight Loss Maintenance, One Year Post-Intervention |
|---------------------------------|-------------------|-----------|-----------|-----------|
| Model                          | Coefficient (SE)  | p-Value   | R-squared | 95% CI    |
| Unadjusted                     |                   |           |           |           |
| Age                            | -.15 (.13)        | 0.25      | 0.03      | -.40, .11 |
| Gender                         | -.03 (2.9)        | 0.99      | 0.00      | -5.8, 5.8 |
| Adjusted                       |                   |           |           |           |
| Age                            | -.21 (.15)        | 0.15      | --        | -.51, .08 |
| Gender                         | -1.5 (3.3)        | 0.66      | --        | -8.2, 5.3 |

N=48 (males=11, females=37)
F test of model significance had F(2, 45)=0.68 and p-value=0.51, Adjusted R-squared=-0.01
Relationships between weight loss maintenance and health perceptions, health habits, physical activity level and online social network habits were further examined using Spearman’s rank order correlation. Participants in the one year post-intervention sample were asked to rate their current health status as well as how their current health status compared to their health status one year ago. They also self-reported weighing frequency, current physical activity pattern, and current use of any online social network. Questions, response choices and response frequencies are seen in Table 4.9.

Table 4.9: Responses to Questions Regarding Health Status, Health Habits and Use of OSN in One Year Post-Intervention Sample

<table>
<thead>
<tr>
<th>Question</th>
<th>Response Choice</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>In general, would you say your health is…</td>
<td>Excellent</td>
<td>10</td>
<td>21.3</td>
</tr>
<tr>
<td></td>
<td>Very good</td>
<td>22</td>
<td>46.8</td>
</tr>
<tr>
<td></td>
<td>Good</td>
<td>12</td>
<td>25.5</td>
</tr>
<tr>
<td></td>
<td>Fair</td>
<td>3</td>
<td>6.4</td>
</tr>
<tr>
<td>Compared to one year ago, how would you rate your health in general now?</td>
<td>Much Better</td>
<td>6</td>
<td>12.8</td>
</tr>
<tr>
<td></td>
<td>Somewhat Better</td>
<td>12</td>
<td>25.5</td>
</tr>
<tr>
<td></td>
<td>About the same</td>
<td>18</td>
<td>38.3</td>
</tr>
<tr>
<td></td>
<td>Somewhat worse</td>
<td>11</td>
<td>23.4</td>
</tr>
<tr>
<td></td>
<td>Much worse</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>How often do you weigh yourself?</td>
<td>Daily</td>
<td>19</td>
<td>41.3</td>
</tr>
<tr>
<td></td>
<td>Weekly</td>
<td>18</td>
<td>39.1</td>
</tr>
<tr>
<td></td>
<td>Monthly</td>
<td>1</td>
<td>2.2</td>
</tr>
<tr>
<td></td>
<td>Not regularly</td>
<td>8</td>
<td>17.4</td>
</tr>
<tr>
<td>What is your current physical activity level as compared to what it was when the study ended?</td>
<td>More active</td>
<td>15</td>
<td>32.6</td>
</tr>
<tr>
<td></td>
<td>Same level</td>
<td>16</td>
<td>34.8</td>
</tr>
<tr>
<td></td>
<td>Less active</td>
<td>15</td>
<td>32.6</td>
</tr>
<tr>
<td>How often do you use an online social network like Facebook?</td>
<td>Daily</td>
<td>15</td>
<td>31.9</td>
</tr>
<tr>
<td></td>
<td>Weekly</td>
<td>12</td>
<td>25.5</td>
</tr>
<tr>
<td></td>
<td>Less than monthly</td>
<td>9</td>
<td>19.2</td>
</tr>
<tr>
<td></td>
<td>Not at all</td>
<td>11</td>
<td>23.4</td>
</tr>
</tbody>
</table>
Responses were tested for separately using Spearman’s correlation to examine strength and direction of relationship to weight maintenance in the one year post-intervention sample (Table 4.10).

Table 4.10: Spearman’s Correlations—Weight Loss Maintenance and Self-Reported Health Status, Self-Monitoring, Physical Activity Level and Current OSN Use

<table>
<thead>
<tr>
<th>Response</th>
<th>N</th>
<th>Spearman’s Rho</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current Health Status</td>
<td>47</td>
<td>0.17</td>
<td>0.25</td>
</tr>
<tr>
<td>Health Compared 1yr ago</td>
<td>47</td>
<td>0.53</td>
<td>0.0001***</td>
</tr>
<tr>
<td>Current Weighing Frequency</td>
<td>45</td>
<td>0.26</td>
<td>0.08</td>
</tr>
<tr>
<td>Current Physical Activity</td>
<td>46</td>
<td>0.42</td>
<td>0.004**</td>
</tr>
<tr>
<td>Current Use of Any OSN</td>
<td>47</td>
<td>-0.23</td>
<td>0.12</td>
</tr>
</tbody>
</table>

*p<0.05, **p<0.01, ***p<0.001

Correlation analysis suggest significant associations between perceived current health status compared to one year ago (over 38% rated their health better) and weight maintenance (p=0.0001). In addition, current self-reported physical activity level appears to be significantly associated with weight loss maintenance one year post-intervention (p=0.004). The relationships between weight loss maintenance at one year post-intervention and perception of current health, self-weighing frequency and use of any online social network were not found to be statistically significant in the subsample.

According to frequency tabulations, 32 of the participants in the subsample (68%) perceived current health status to be “very good” or “excellent,” one year post-intervention. When asked to compare current health status to health status one year ago (at study completion), 18 (38%) rated their health as “somewhat better” or “much better.” Current weight frequency was reported as “daily” or “weekly” for 37 participants (80%) in the one year post-intervention sample. In terms of current physical activity level
compared to activity level at study completion, 31 participants (67%) reported the “same level” of activity or “more activity”.

Spearman’s correlations were also used to examine associations between perceptions of benefit from study participants and resultant weight loss maintenance. At one year post-intervention, participants used a 5-point scale (strongly agree, agree, neutral, disagree, strongly disagree) to indicate level of agreement to the following statements:

- Participating in the iWell study improved my health.
- Participating in the iWell study helped me achieve my health goals.
- Tracking my physical activity during the study had a positive impact on my health.
- Tracking my weight over the course of the study had a positive impact on my health.
- Tracking my lab values and measurements had a positive impact on my health.
- “Friending” and having friends on the social network had a positive impact on my health.
- Being able to post on the social network had a positive impact on my health.
- Being able to make comments on the social network had a positive impact on my health.
- Engaging in competitions on the social network had a positive impact on my health.

Results of the correlation analyses are seen in Table 4.11.
Table 4.11: Spearman’s Rank Order Correlations—Perceptions of Study Benefit and Weight Loss Maintenance

<table>
<thead>
<tr>
<th>Statement</th>
<th>N</th>
<th>Spearman’s Rho</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>iWell improved Health</td>
<td>47</td>
<td>0.28</td>
<td>0.06</td>
</tr>
<tr>
<td>iWell helped reach health goals</td>
<td>45</td>
<td>0.27</td>
<td>0.08</td>
</tr>
<tr>
<td>Tracking Activity had positive health impact</td>
<td>46</td>
<td>0.22</td>
<td>0.14</td>
</tr>
<tr>
<td>Tracking weight had positive health impact</td>
<td>47</td>
<td>0.18</td>
<td>0.23</td>
</tr>
<tr>
<td>Tracking lab values had positive health impact</td>
<td>47</td>
<td>0.20</td>
<td>0.17</td>
</tr>
<tr>
<td>“Friending” had positive health impact</td>
<td>46</td>
<td>-0.05</td>
<td>0.77</td>
</tr>
<tr>
<td>Posting had positive health impact</td>
<td>46</td>
<td>-0.12</td>
<td>0.41</td>
</tr>
<tr>
<td>Commenting had positive health impact</td>
<td>46</td>
<td>-0.17</td>
<td>0.27</td>
</tr>
<tr>
<td>Competitions on OSN had positive health impact</td>
<td>46</td>
<td>-0.23</td>
<td>0.13</td>
</tr>
</tbody>
</table>

Response Choices: Strongly Agree, Agree, Neutral, Disagree, Strongly Disagree

Overall, statistical analyses did not indicate any significant associations between perceptions of study benefit and weight loss maintenance one year post-intervention. However, frequency tabulations suggest that a majority of the sample perceived benefit from participation, as seen in Table 4.12.
Table 4.12: Frequency Tabulations—Perceptions of Benefit from Study Participation

<table>
<thead>
<tr>
<th>Statement</th>
<th>Response Choice</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>iWell improved health</td>
<td>Strongly agree</td>
<td>7</td>
<td>14.9</td>
</tr>
<tr>
<td></td>
<td>Agree</td>
<td>31</td>
<td>66</td>
</tr>
<tr>
<td></td>
<td>Neutral</td>
<td>8</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td>Disagree</td>
<td>1</td>
<td>2.1</td>
</tr>
<tr>
<td></td>
<td>Strongly disagree</td>
<td></td>
<td></td>
</tr>
<tr>
<td>iWell helped reach health goals</td>
<td>Strongly agree</td>
<td>5</td>
<td>11.1</td>
</tr>
<tr>
<td></td>
<td>Agree</td>
<td>28</td>
<td>62.2</td>
</tr>
<tr>
<td></td>
<td>Neutral</td>
<td>9</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>Disagree</td>
<td>3</td>
<td>6.7</td>
</tr>
<tr>
<td>Tracking Activity had positive health impact</td>
<td>Strongly agree</td>
<td>16</td>
<td>34.8</td>
</tr>
<tr>
<td></td>
<td>Agree</td>
<td>27</td>
<td>58.7</td>
</tr>
<tr>
<td></td>
<td>Neutral</td>
<td>2</td>
<td>4.4</td>
</tr>
<tr>
<td></td>
<td>Strongly disagree</td>
<td>1</td>
<td>2.1</td>
</tr>
<tr>
<td>Tracking weight had positive health impact</td>
<td>Strongly agree</td>
<td>9</td>
<td>19.2</td>
</tr>
<tr>
<td></td>
<td>Agree</td>
<td>31</td>
<td>66</td>
</tr>
<tr>
<td></td>
<td>Neutral</td>
<td>5</td>
<td>10.7</td>
</tr>
<tr>
<td></td>
<td>Disagree</td>
<td>1</td>
<td>2.1</td>
</tr>
<tr>
<td></td>
<td>Strongly disagree</td>
<td>1</td>
<td>2.1</td>
</tr>
<tr>
<td>Tracking lab values had positive health impact</td>
<td>Strongly agree</td>
<td>13</td>
<td>27.7</td>
</tr>
<tr>
<td></td>
<td>Agree</td>
<td>28</td>
<td>59.6</td>
</tr>
<tr>
<td></td>
<td>Neutral</td>
<td>6</td>
<td>12.7</td>
</tr>
<tr>
<td>“Friending” had positive health impact</td>
<td>Strongly agree</td>
<td>3</td>
<td>6.5</td>
</tr>
<tr>
<td></td>
<td>Agree</td>
<td>12</td>
<td>26.1</td>
</tr>
<tr>
<td></td>
<td>Neutral</td>
<td>19</td>
<td>41.3</td>
</tr>
<tr>
<td></td>
<td>Disagree</td>
<td>8</td>
<td>17.4</td>
</tr>
<tr>
<td></td>
<td>Strongly disagree</td>
<td>4</td>
<td>8.7</td>
</tr>
<tr>
<td>Posting had positive health impact</td>
<td>Strongly agree</td>
<td>3</td>
<td>6.5</td>
</tr>
<tr>
<td></td>
<td>Agree</td>
<td>10</td>
<td>21.7</td>
</tr>
<tr>
<td></td>
<td>Neutral</td>
<td>20</td>
<td>43.5</td>
</tr>
<tr>
<td></td>
<td>Disagree</td>
<td>9</td>
<td>19.6</td>
</tr>
<tr>
<td></td>
<td>Strongly disagree</td>
<td>4</td>
<td>8.7</td>
</tr>
<tr>
<td>Commenting had positive health impact</td>
<td>Strongly agree</td>
<td>1</td>
<td>2.2</td>
</tr>
<tr>
<td></td>
<td>Agree</td>
<td>9</td>
<td>19.6</td>
</tr>
<tr>
<td></td>
<td>Neutral</td>
<td>22</td>
<td>47.8</td>
</tr>
<tr>
<td></td>
<td>Disagree</td>
<td>11</td>
<td>23.9</td>
</tr>
<tr>
<td></td>
<td>Strongly disagree</td>
<td>3</td>
<td>6.5</td>
</tr>
<tr>
<td>Competitions on OSN had positive health impact</td>
<td>Strongly agree</td>
<td>8</td>
<td>17.3</td>
</tr>
<tr>
<td></td>
<td>Agree</td>
<td>17</td>
<td>37</td>
</tr>
<tr>
<td></td>
<td>Neutral</td>
<td>13</td>
<td>28.3</td>
</tr>
<tr>
<td></td>
<td>Disagree</td>
<td>4</td>
<td>8.7</td>
</tr>
<tr>
<td></td>
<td>Strongly disagree</td>
<td>4</td>
<td>8.7</td>
</tr>
</tbody>
</table>
Thirty eight participants (80%) in the subsample agreed or strongly agreed that participating in the study improved their health. In addition, 33 participants (70%) agreed or strongly agreed that participating in the study helped them achieve health goals. In terms of the tracking features of the study design, 43 participants (93%) believed that tracking physical activity over the course of the study had a positive impact on their health. Forty participants (85%) and 41 participants (87%), respectively, agreed or strongly agreed that tracking weight and lab values over the course of the study had a positive impact on their health. Online social network features of friending, posting and commenting appeared to have the least perceived benefit, according to the sample responses, with most participants perceiving these features to have neutral benefit at best. Engaging in competitions was perceived to have a positive impact on health for 25 of the participants (54%). Though lacking statistical significance and reflective of the subsample only, the empirical findings suggest that one year post-intervention, participants perceived benefit from study participation and rated tracking features of the study as having a positive impact on health.

Secondary Research Hypothesis

_Cardiovascular and metabolic disease risk factors differed from baseline to one year post-intervention and varied according to age, gender, perceptions of health, current self-monitoring and physical activity levels._

The findings from the 6-month study did not show improvements in risk markers for cardiovascular and metabolic disease (LDL, insulin resistance, fasting blood glucose, HbA1c). Although the follow-up analysis was not powered to detect differences in these
markers, data were available to examine changes in cardiovascular and metabolic risk markers between baseline and one year post-intervention in the subsample of participants.

To test for significant differences in cardiovascular and metabolic disease marker variables (LDL, HDL, triglycerides, fasting blood glucose and HbA1c) from mean baseline values to one year post-intervention values, paired t-tests were used (Table 4.13).

Table 4.13: Paired t-tests—Change in Continuous Variables from Baseline to One Year Post-Intervention

<table>
<thead>
<tr>
<th>Risk Marker</th>
<th>Mean (SD)</th>
<th>p-Value</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>LDL (mg/dl)</td>
<td>8.8 (25.5)</td>
<td>0.99</td>
<td>1.4, 16.1</td>
</tr>
<tr>
<td>Triglycerides (mg/dl)</td>
<td>-8.9 (37.2)</td>
<td>0.05</td>
<td>-19.7, 1.9</td>
</tr>
<tr>
<td>HDL (mg/dl)</td>
<td>.27 (9.4)</td>
<td>0.42</td>
<td>-2.5, 3.0</td>
</tr>
<tr>
<td>IRR (Trig/HDL)</td>
<td>-.18 (.84)</td>
<td>0.07</td>
<td>-.42, .06</td>
</tr>
<tr>
<td>Fasting BG (mg/dl)</td>
<td>2.67 (22.2)</td>
<td>0.8</td>
<td>-3.7, 9.2</td>
</tr>
<tr>
<td>HbA1c (%)</td>
<td>-.10 (.39)</td>
<td>0.04*</td>
<td>-.22, .01</td>
</tr>
</tbody>
</table>

Note: IRR=Insulin Resistance Ratio (Trig/HDL)
N=48 (males=11, females=37)
*p<0.05, **p<0.01, ***p<0.001

These results show the mean change in HbA1c to be statistically significant (p<0.05) indicating improved blood glucose control and reduced metabolic disease (diabetes) risk. Risk markers of diabetes (triglycerides and insulin resistance ratio) decreased, but the reductions were not statistically significant. Fasting blood glucose increased between the two time periods as did LDL cholesterol, a marker for cardiovascular disease.

To test for proportional differences in the same risk markers, McNemar’s test was used. Cardiovascular and metabolic disease risk markers of LDL cholesterol, insulin resistance ratio (triglycerides/HDL), fasting blood glucose and HbA1c at baseline and at one year post-intervention were compared in the subsample of 48. All risk markers were
coded “normal” or “abnormal” based on established guidelines for the clinical identification of risk for cardiovascular disease and diabetes (Lloyd-Jones, et al., 2009; American Diabetes Association, 2013). Results of the proportional comparison are shown in Table 4.14.

Table 4.14: McNemar’s Test of Proportions—Participants with Normal Cardiovascular and Metabolic Disease Risk Markers at Baseline, 6 Months and One Year Post-Intervention

<table>
<thead>
<tr>
<th>Risk Marker</th>
<th>Baseline</th>
<th>6-Mos</th>
<th>1 Yr Post</th>
<th>Change in Proportion</th>
<th>95% CI</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>LDL (mg/dl)</td>
<td>30</td>
<td>28</td>
<td>28</td>
<td>-.04</td>
<td>-.19, .11</td>
<td>0.53</td>
</tr>
<tr>
<td>IRR (Trig/HDL)</td>
<td>28</td>
<td>28</td>
<td>34</td>
<td>.13</td>
<td>-.03, .28</td>
<td>0.08</td>
</tr>
<tr>
<td>FBG (mg/dl)</td>
<td>31</td>
<td>33</td>
<td>36</td>
<td>.10</td>
<td>0.00, .21</td>
<td>0.03*</td>
</tr>
<tr>
<td>HbA1c (%)</td>
<td>33</td>
<td>30</td>
<td>38</td>
<td>.10</td>
<td>-.05, .26</td>
<td>0.13</td>
</tr>
</tbody>
</table>

N=48 (males=11, females=37)

Note: Normal—LDL<130mg/dl, IRR<=2.1, FBG<100mg/dl, HbA1c<5.7%
*p<0.05, **p<0.01, ***p<0.001

According to these results, the proportion of participants with normal LDL was not found to be significantly different one year post-intervention compared to baseline (p=0.53). In fact, the proportion of participants with normal LDL decreased 4%, effectively increasing risk status in the subsample. Fasting blood glucose was the only metabolic disease risk factor found to be significantly different one year post-intervention compared to baseline was fasting blood glucose (p=0.03). This finding is equivalent to a 10% increase in the proportion of participants with normal values at one year post-intervention compared to baseline values. Insulin resistance and HbA1c were not found to be significantly different one year post-intervention as compared to baseline, although the proportion of participants with normal values increased in both cases (13% increase for insulin resistance and 10% increase for HbA1c). McNemar’s test of proportions was used to
examine gender differences, with no significant proportional differences seen in any of the risk markers for males or females.

By empirical observation, risk status one year post-intervention moved in a favorable direction for all risk factors except LDL cholesterol. At baseline, 63% of the sample exhibited normal levels of LDL cholesterol, compared to 58% at one year post-intervention. Fifty eight percent of the sample had normal insulin resistance values at baseline, compared to 71% at one year post-intervention. Normal blood glucose was observed in 65% of participants at baseline and 75% one year post-intervention. Normal HbA1c markers were seen in 69% of the sample at baseline compared to 79% one year post-intervention. Despite unknown influences from other factors in the time period between study completion and one year post-intervention, this trend suggests risk reduction in the sample population.

To examine whether these changes in risk factor profile at one year post-intervention were associated with age, gender, perception of health, current self-monitoring habits, and current physical activity level linear and multiple regression models were used. Abbreviated results for both models are presented in Table 4.15.
<table>
<thead>
<tr>
<th>Predictor</th>
<th>LDL</th>
<th>Insulin Resistance</th>
<th>Fasting Blood Glucose</th>
<th>HbA1c</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single Variable Model</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td>Multiple Variable Model</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single Variable Model</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td>Multiple Variable Model</td>
<td>p=0.03*</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td><strong>Current Health Status</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single Variable Model</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td>Multiple Variable Model</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td><strong>Current Weight Freq.</strong></td>
<td></td>
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<tr>
<td>Single Variable Model</td>
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<tr>
<td>Multiple Variable Model</td>
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<tr>
<td><strong>Current Physical Activity</strong></td>
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<tr>
<td>Single Variable Model</td>
<td>NS</td>
<td>p=0.02*</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td>Multiple Variable Model</td>
<td>NS</td>
<td>p=0.03*</td>
<td>NS</td>
<td>NS</td>
</tr>
</tbody>
</table>

NS=Not Significant

In the multiple regression model, females demonstrated a slight increase in LDL level, pointing toward higher cardiovascular risk for women. Current physical activity level was self-reported by the sample participants, as either “more active,” “less active,” or “the same” level as compared to 6-month study completion. This variable was found to be significantly associated with insulin resistance in both regression models, strengthening the rationale for maintaining this physical activity as a modifying risk reduction strategy. The age of the participant, their perceived health status (current and one year ago), and frequency of self-monitoring of weight were not found to be associated with changes in risk markers at one year post-intervention in either of the regression models.
In summary, statistically significant risk reduction was observed in the subsample as measured from baseline to one year post-intervention for the metabolic disease marker of insulin resistance. Significant associations between predictive variables and risk marker change were seen for females (negative association, with LDL increase) and for current physical activity (positive association with insulin resistance decrease). Cardiovascular and metabolic disease risk reduction in the subsample could not be predicted according to age, perceptions of health status, or current self-monitoring habits, at one year post-intervention.
Chapter 5

Discussion and Conclusions

This chapter is designed to present findings related to the primary and secondary research hypotheses, highlight implications for public health, discuss limitations, and provide recommendations for future research studies.

In spite of decades of interventions aimed at weight loss and maintenance, obesity is arguably one of the greatest threats to the public’s health, affecting Americans of all ages, ethnicities and socioeconomic levels. Currently, a majority of U.S. adults and a considerable proportion of children and adolescents are categorized as overweight or obese (Flegal, Carroll, Ogden, & Curtin, 2012). This translates to an estimated 73 million American adults and 12 million children and adolescents already obese. Those categorized as overweight are likely to become obese if they gain weight over time.

Despite years of prevention and treatment efforts, prevalence of obesity is projected to increase in the U.S. and worldwide, with health, social and economic burdens that are likely to be devastating. Solving the obesity problem has been a focal point for health professionals for many years yet little progress has been made to alter the trajectory of the epidemic.

Numerous strategies have been tested to determine what works in helping people lose weight. Those that seem to be the most effective have focused on motivational and behavioral factors such as exercise, self-monitoring, and social support (Turk, et al., 2012; Silva, et al., 2011; Leahey, Kumar, Weinberg, & Wing, 2012). Regular, structured physical activity is a lifestyle strategy incorporated into nearly all weight loss
interventions and is a factor strongly associated with short-term weight loss (Ashmore, Frierson, & Blair, 2012). Self-monitoring of exercise, diet and weight has also been strongly associated with achieving weight loss (Burke, Wang, & Sevick, 2011; Brindal, Freyne, Saunders, Berkovsky, Smith, & Noakes, 2012). In addition, involving friends and family in weight loss efforts is associated with improved outcomes (Kiernan, et al., 2012; Gorin, Sherwood, Jeffrey, Phelan, Tate, & Wing, 2005). These strategies have been repeatedly used in weight loss interventions and have proven effective in the short-term, but unfortunately fail to provide evidence for sustained weight loss.

Treatment non-adherence, cost, changes in physical activity level, self-weighing habits, behavioral and psychosocial factors have been cited as possible reasons for poor long-term outcomes (Winnet, Tate, Anderson, Wojcik, & Winett, 2005; Butryn, Phelan, Hill, & Wing, 2007). Whereas weight management is a life-long endeavor for many, intervention models are often 6 months in duration. Few intervention trials follow participants beyond 1 year, demonstrating as high as 37% sustained weight loss of 10% or more (Kraschnewski, et al., 2010). With lack of structure and support in an obesogenic environment, the evidence suggests that a majority of successful short-term weight losers will likely regain weight over time.

As an alternative to costly and inconvenient in-person models, recent research efforts including the iWell randomized clinical trial have increasingly relied on technology-based intervention designs. Based on similar motivational and behavioral constructs as in-person intervention models, these web-based approaches have the
potential for rapid and widespread dissemination and could provide a new framework for health professionals to more effectively thwart escalating health conditions such as overweight and obesity, on a population level. Key components of successful technology-based interventions have been described by Khaylis, Yiaslas, Bergstron and Gore-Felton (2010) and include self-monitoring devices (physical activity, weight, diet trackers), online feedback and online social network support. Thus far, intervention designs have incorporated these types of features in varying and inconsistent ways, and the reviews of such approaches have been mixed. Interventions that seem to be most effective have incorporated activity tracking devices to motivate behavior change resulting in statistically significant weight loss (Pellegrini, Verba, Otto, Helsel, Davis, & Jakicic, 2011; Catenacci, Grunwald, Ingebrigtsen, Jakicic, McDermott, & Phelan, 2010). However, a recent review of technology-based interventions by Wieland and colleagues (2012) concluded that at best, these approaches were better than self-directed care, but not as effective as in-person treatment. In essence, the potential for weight loss appears to be greater if some degree of personal contact is part of the intervention design. Such conflicting results add to the challenge of addressing an important and escalating health threat such as obesity. More research is necessary to determine whether selected technology-based strategies may work in selected populations, and what factors influence success.

Past research by Harvey-Berino, Pintauro, and Gold (2002) provided evidence that the internet could be used as an alternate delivery method for weight loss intervention. Subsequent studies, built on web-based delivery platforms, added diet
tracking features and activity tracking devices (Richardson, Newton, Abraham, Sen, Jimbo, & Swarz, 2008; King, Ahn, Oliveira, Atienza, Castro, & Gardner, 2008; Atienza, Oliveira, Fogg, & King, 2006). These technology features required participants to regularly upload data from the devices to a website, and provided opportunities for participants to receive more timely (often immediate) feedback. These approaches, whether by design or serendipity, were drawn from established behavioral theory constructs that have been associated with successful weight loss—self-regulation, self-efficacy, and self-determination (Shin, Shin, Liu, Dutton, Abood, & Ilich, 2011; Rejeski, Mihalko, Ambrosius, Bearon, & McClelland, 2011). Other approaches have combined social support and technology in weight loss intervention designs, finding that participants who were part of a team or enrolled in a competition were more likely to lose weight than those that participated on an individual basis (Buis, et al., 2009; Gokee Larose, Leahey, Weinberg, Kumar, & Wing, 2012).

The present study used secondary data from a recent technology-based weight loss intervention involving overweight adult healthcare workers, and examined the factors that influenced short and longer term weight loss and health improvement outcomes. Data was used from the iWell Randomized Clinical Trial, 6-month health improvement and weight loss intervention conducted in a healthcare setting in Springfield, Oregon. The study enrolled 500 healthcare workers, primarily White women over the age of 50. Participants were randomized into either a control (self-directed) group or an experimental (technology-enabled) group. A total of 165 control participants and 168 experimental participants (66%) completed the 6-month intervention. At one
year post-intervention, data was collected on a subsample of the 168 technology-enabled participants (n=48) to examine longer term outcomes, in particular, weight loss maintenance and change in cardiovascular and metabolic risk markers.

Previous findings examined 6-month outcomes in the iWell trial, comparing self-directed participants to technology-enabled participants and found greater weight loss and increases in physical activity in the technology-enabled participants compared to the self-directed participants (Greene, Sacks, Piniewski, Kil, & Hahn, 2012). Although results from the iWell study provided important information about the short-term impact of technology on weight loss intervention, it was not designed to draw conclusions about characteristics of the technology users, extent of technology use, specific features of technology that were predictive of success, or of longer term effectiveness.

For the purposes of this research, data from the 168 technology-enabled participants were used to examine predictors associated with weight loss and health improvement, at the end of the 6-month study and in a subsample (n=48) at one year post-intervention. Variables of interest for analysis of the 6-month data were demographic characteristics (age, gender), clinical indicators of cardiovascular and metabolic risk (BMI, LDL, triglycerides, HDL, blood glucose, and HbA1c), and utilization of technology features (activity uploaded, weight uploads, online social network activity). Weight loss (% BMI change) was the primary outcome of interest. These same variables were used for the one year post-intervention analysis in addition to self-reported qualitative data regarding perceptions of health status, current self-
monitoring, physical activity habits and online social network use, and perceptions of study benefit. The results of these analyses will be useful in developing a framework for refinement and design of future weight loss studies that include technology features such as tracking devices and online social networking.

Similar to previous research findings, the present study found significant relationships between using technology features and weight loss. Specifically, this study found that those that tracked weight and activity demonstrated greater weight loss than those that used the technology features less. Utilization of the social network was also associated with weight loss, to a lesser degree and only for male participants. Based on these findings, it appears that using technology features to track activity and weight provided the necessary motivation for behaviors that lead to modest, sustainable weight loss. There are important factors to consider that may have influenced the results. These include the relatively small sample size of technology-enabled participants, the source population (healthcare workers who were interested in improving health), the lack of a structured dietary component, and lower than expected utilization of the online social network. Despite this, the findings of this study provide a rationale for integrating technology features into weight loss interventions, particularly technology designed for tracking and monitoring physical activity and weight.

The following section discusses key findings from the study as related to each research hypotheses tested.
Differences in weight loss in technology-enabled participants will be predicted by age, gender, disease burden and overall utilization of the online social network.

Previous research has associated selected demographic characteristics such as participant age with use of technology designed track physical activity and diet. King, et al., and Atientza (2008) and Oliveira, Fogg and King (2006) studied adults over the age of 50 who had little previous experience with self-monitoring devices and found that by using electronic activity and dietary tracking devices, behavior change would occur and health improvements would result. In their purely web-based weight loss intervention, Brindal, Feyne, Saunders, Berkovsky, Smith and Noakes (2012) found older participants (65 years or older) were more likely to use the website more often, reasoning that they had more free time available than younger counterparts in the sample. Based on these findings, the present analysis was designed to determine if age of participant influenced weight loss. However, the results of the analysis showed no differences in weight loss according to age (p=0.08). This finding may be inconsistent with previous research based on the fact that technology is increasingly being used for everyday tasks, by persons of all ages. Today, adults over the age of 50—particularly those that work in a technology oriented environment such as a healthcare organization—are much more likely to have experience with interactive technology as compared to adults over the age of 50 in the year 2008.

In terms of gender, the findings of this study did not expose any significant differences in weight loss based on gender. One of the technology features in the iWell
study was a designated online social network, designed to facilitate social support among the technology-enabled participants. According to a recent Pew Internet report (Fitzgerald, 2012) online social networks like Facebook and Pinterest are used more by women than men. The present analysis attempted to determine if gender influenced weight loss outcomes. Findings indicated a low probability that gender could predict weight loss (p=0.75). Regression models (single and multiple variable) that included age and gender did not reach statistical significance. Of note, the majority of participants in the 6-month study were women, aged 50 years or older. The overall age range was wide, ranging from 24 years to 72 years. The uneven distribution of gender and the wide age range—typical of many healthcare settings—may have precluded the ability to detect any meaningful differences based on these two characteristics. A study design with a larger N that includes a more even distribution of demographic characteristics would strengthen findings related to age and gender.

In terms of disease burden, previous research by (Brindal, Freyne, Saunders, Berkovsky, Smith, & Noakes, 2012) has suggested that disease burden (as indicated by baseline BMI) can predict weight loss. As dictated by the iWell study protocol, participants received copies of risk marker results (BMI, LDL, triglycerides, HDL, blood glucose, HbA1c) and interpretations immediately after baseline, 3 month and 6 month assessments. Values were uploaded to individual dashboards and color coded for risk level (green=low risk, yellow=medium risk, red=high risk), providing risk status information to the participants. Only participants with high level risk markers were referred for follow-up with a primary care physician. Although all subjects had website
access to information regarding risk factor modification, it is not known how many
accessed those resources or whether they understood how those values translated into
their own personal disease burden. These factors may have influenced the results of the
analysis, which did not find disease burden (as represented by baseline BMI, insulin
resistance and HbA1c) to be predictive of weight loss. In other words, participants with
abnormal baseline biomarkers were no more likely to lose weight than those with normal
baseline values.

After testing with single and multivariate regressions models, participants with a
high disease burden did not lose significantly more weight than those that with a lower
disease burden according to baseline risk markers. In the multiple regression model, p-
values for baseline BMI, baseline insulin resistance and baseline HbA1c were 0.75, 0.75
and 0.80 respectively, indicating low predictive power related to weight loss. When these
same disease burden variables were tested according to gender, no differences were seen
in weight loss according to baseline BMI, insulin resistance ratio and HbA1c levels in
males or females. Thus, disease burden did not influence weight loss outcomes,
independent of gender. These findings may have limited value, as it is not known how
whether risk status was apparent to the participants, in spite of written lab results and
interpretations and visual cues on the website. This illustrates an opportunity for future
studies to consider additional educational measures and assessments of health risk
knowledge as related to markers of overweight and obesity. Such a design would allow a
more accurate examination of the influence of risk perceptions on weight loss outcomes.
Previous social science and behavioral research has recognized the importance of social support in behavior change interventions (Uchino, 2004; Cohen & Syme, 1985; Berkman, 1995), but little is known about the influence of virtual (online) social support as part of a multi-component weight loss intervention. Therefore, the online social network (OSN) feature of the iWell intervention was of special interest as a possible predictor of weight loss. The OSN design was similar to Facebook in that participants could “friend” each other, post comments, and comment on other posts. As with Facebook, the user could control privacy settings, determining who could access information on their page (including progress made toward health improvement). Despite using a template similar to the widely popular Facebook, the analysis failed to find total use (sum of friend requests, posts, comments) of the iWell OSN predictive of weight loss for the intervention group as a whole (p=0.32 in the single variable regression and p=0.26 in the multiple variable regression). This result may have been due to the overall low utilization of the OSN. Of note, during the 6-month period, participants used OSN was an average of 11.2 times. Considering the average adult Facebook user sends 9 messages a month (Brenner, 2012), the utilization of the iWell OSN was well-below average, with only 11.2 OSN activities documented over the 6-month study period. When gender differences were examined, total OSN use was a significant predictor of weight loss for males as compared to females. This finding should be interpreted with caution due to the overall low utilization of the OSN. It is however notable, as males comprised the minority of participants in the iWell study, and as previously stated, are less likely to use online social networks (such as Facebook, Pinterest, Twitter) as
compared to females (Zickurh & Smith, 2012). Though the strength of this finding is questionable, it is still suggestive that males may be a potential target population for health improvement interventions that include OSNs.

*Differences in weight loss will be predicted by nature and extent of selected technology features.*

Part of the analyses focused on specific technology feature utilization during the intervention. The features of interest were uploads from the activity tracker and the scale, and active utilization of the online social network. The findings suggest these features were the most significant predictors of weight loss (p=0.001 for activity uploaded and p<0.001 for weight uploads). Simply put, this study found participants who used the tracking features more, lost more weight. As individual features, uploading activity and total count of weight uploads were predictive of weight loss, for both males and females. In the multivariate analyses, the statistical significance held for these two variables, confirming findings from other technology-based weight loss interventions that have found significant relationships between self-monitoring of weight and physical activity and weight loss (Brindal, Freyne, Saunders, Berkovsky, Smith, & Noakes, 2012; Burke, et al., 2011). As seen in previous research, these findings support intervention designs that emphasize building self-regulatory skills that can facilitate weight loss (Turk, et al., 2012; Wing, Tate, Gorin, Raynor, & Fava, 2006). Self-monitoring is a means of self-regulation, and the physical activity and weight monitoring features used by the
intervention participants appeared to facilitate those self-regulation skills, with resultant weight loss.

As noted previously, utilization of the OSN was not found to be significantly associated with weight loss as a single variable. As seen in the multiple regression model, utilizing the OSN was associated with weight loss for males but not females. Again the overall low use of the OSN (participants used the OSN an average of 11.2 times in the six-month period) should be noted when considering the implication of these findings. Interventions that document greater OSN engagement may have greater potential to understand what motivates the use of OSN technology features throughout a study period.

The findings of this study suggest that males are more likely to use certain technology features more than females, particularly technology devices that provided feedback about activity and weight. With respect to the use of the tracking devices, males were more likely to upload physical activity and weight information than females over the course of the 6-month intervention. Males uploaded weight 48 times versus 35 for females, and uploaded 755 miles compared to 453 for females. This finding suggests a possible gender-based technology use difference, previously introduced by Venkatesh, Thong and Xu (2012). In looking at factors related to consumer use of technology, these researchers found distinct differences in strength and activation of habit that varied across age, gender and experience. For behavioral researchers, this may be an important area to
assess to optimize utilization of selected technology features and devices based on gender differences.

*Weight loss maintenance in technology-enabled participants was maintained from baseline to one year post-intervention.*

As numerous other studies have found, traditional in-person behavioral weight loss interventions yield effective short-term results, but successful weight loss maintenance beyond one year is rare (Witham & Avenell, 2010; Svetkey, et al., 2008). In the literature, weight loss maintenance is inconsistently defined. According to some, a 10% reduction in body weight that is maintained for at least one year is considered weight loss maintenance (Kraschnewski, et al., 2010; Wing & Hill, 2001). Others point to the maintenance of a percentage original weight loss, as measured 1, 2, or more years after intervention completion as the indicator of weight loss maintenance (Anderson, Konz, Frederich, & Wood, 2001; Barte, et al., 2010).

In the present study, weight loss maintenance is defined as BMI reduction of at least 3% maintained from baseline to one year post-intervention. This definition is largely based on the fact that modest weight loss of 3-5%, maintained for one year, has been associated with improvements in HDL cholesterol, triglycerides, glucose metabolism and reduced risk of cardiovascular disease (Donnelly, Blair, Jakicic, Manore, Rankin, & Smith, 2009).

Body mass index data from the subsample (n=48) was available at baseline, 6-month study completion, and one year post-intervention. Weight loss from baseline to 6-
months (end of study) was evidenced by a -3.2\% reduction in BMI, achieving statistical significance (p<0.0001). From 6-month study completion to one year post-intervention, a BMI change of -1.5\% was seen. Though not statistically significant, this finding indicates continued weight loss beyond study completion, in the subsample.

The key finding related to longer term weight loss was the result of the analysis of BMI change from baseline to one year post-intervention. In the subsample, this measure was found to be significant, with a -4.7\% decrease noted (p=0.001), indicating achievement of weight loss maintenance longer term. Unlike findings from previous studies, where failure to maintain weight lost during the intervention suggests a typical pattern of gradual weight regain, these findings indicate weight loss was maintained and moderately accentuated over time, by the participants in the subsample.

*Weight loss maintenance at one year post-intervention could be predicted by age, gender, perceptions of benefit, current health status, activity levels, and self-monitoring.*

Data collected at one year post-intervention included repeat measures of the same biomarker and biometric assessments done during the intervention, as well as self-reported information regarding current health status and habits. This made it possible to explore how these factors influenced longer term outcomes. The one year post-intervention analyses examined associations between age and gender as well as perceptions of health, current weight monitoring and physical activity habits and current OSN use. Of note, the one year sample was slightly older than the 6-month sample (54 years versus 50 years) and was comprised of similar, uneven gender distributions (23\%
males, 77% females). In the subsample analysis, age and gender were not found to be predictive of weight loss maintenance one year post-intervention. Both variables were tested separately and in a multiple regression model, with no statistically significant associations identified.

At one year post-intervention, perceived health status, current self-monitoring, current physical activity levels and current use of an OSN were expected to be correlated with weight loss maintenance. Despite 68% of the sample reporting current health to be very good or excellent, this perception of current health did not statistically correlate with weight loss maintenance one year post-intervention. When asked to compare current health status to health status one year ago (equivalent to 6-month study completion), over 38% of the sample rated current health as better than one year ago, and this finding showed statistical significance (p<0.001). Current weight frequency was of interest since frequent self-monitoring of weight is a factor associated with successful weight loss maintenance (Brindal, Freyne, Saunders, Berkovsky, Smith, & Noakes, 2012; Van Wormer, French, Pereira, & Welsh, 2008). In the one year post-intervention subsample, 80% of the respondents reported weighing on a daily or weekly basis. Though the analysis suggested an empirical correlation between this habit and resultant weight loss maintenance, the actual statistic did not reach a level of significance (p=0.08). The other factor showing statistical significance was self-reported current physical activity. Sixty seven percent of the sample reported engaging in the same level of physical activity or more as compared to the end of study time period, and this demonstrated statistical significance as well (p<0.01). Perceived current health status and current use of any
online social network did not appear to be correlated with weight loss maintenance one year post-intervention.

This analysis attempted to determine if specific technology features (tracking weight, activity, lab values and different features of the online social network) were of value to the technology-enabled participants and did they correlate with outcomes of practical importance. Correlation analyses failed to find any significant associations between ratings of these features and weight loss maintenance. Respondents generally believed that participating in the iWell study improved their health and helped them reach their health goals, with results of the correlation trending toward a positive association, though not statistically significant (p=0.06 for health improvement and p=0.08 for reaching health goals).

Though correlation analyses did not reach statistical significance, according to frequency tabulations, the vast majority of the subsample (80%) agreed or strongly agreed that participating in the iWell study improved health and help achieved health goals. Tracking physical activity, weight and lab values was also reported to have a positive impact on health by over 85% of the participants. Features related to the online social network were not felt to have a positive impact on health, according to the frequency tabulations. Thirty three percent of the sample agreed or strongly agreed that “friending” had a positive impact on health, 28% agreed or strongly agreed that posting had a positive impact on health, and 22% agreed or strongly agreed that commenting had a positive impact on health. Of the sample, 57% agreed or strongly agreed that engaging
in competitions had a positive impact on health. Though not found to be statistically correlated with weight loss outcomes in this analysis, this particular finding is consistent with previous work that has associated successful weight loss with team membership and engagement in competitions (Leahey, Kumar, Weinberg, & Wing, 2012; Buis, et al., 2009; Wing, Pinto, Crane, Kumar, Weinberg, & and Gorin, 2009) and is worthy of further study.

Cardiovascular and metabolic disease risk factors differed from baseline to one year post-intervention and varied according to age, gender, perceptions of health, current self-monitoring and physical activity levels.

No significant differences were noted in risk markers of technology-enabled participants at 6 months (Greene, Sacks, Piniewski, Kil, & Hahn, 2012). At one year post-intervention, repeated measures were used to collect information on the biomarkers of interest that were used during the 6-month intervention, allowing for an examination of differences in cardiovascular and diabetes risk markers from baseline to one year post-intervention. During the intervention, the focus was on increasing physical activity and weight loss, and the iWell investigators did not expect to detect significant differences in these markers in the short-term. The question remained, one year after the intervention ended, would risk reduction patterns be detectable and, if so, would they be associated with personal characteristics, health perceptions or current health habits? According to t-tests performed on the continuous variables of LDL, HDL, triglycerides, fasting blood glucose and HbA1c, only the mean change in HbA1c was statistically different from
baseline to one year post-intervention (p<0.05). The average decrease in HbA1c was -0.10%. This reduction has important clinical implications for diabetes risk reduction, as the mean HbA1c in the sample was 5.7% at baseline and 6-month study completion. A normal HbA1c is 5.6% or less (Medline Plus, 2013), therefore this finding indicates diabetes risk in the subsample reduced to a level of clinical as well as statistical significance.

After coding paired risk factor variables of LDL, insulin resistance, blood glucose and HbA1c (from baseline and one year post-intervention time points) “normal” or “abnormal” based on clinical practice guidelines for the identification of cardiovascular and metabolic disease risk (NHLBI 2012; American Diabetes Association, 2013), McNemar’s test was used to identify statistically significant proportional changes in the subsample from baseline to one year post-intervention. At one year post-intervention these analyses found significant proportional change in the risk marker of fasting blood glucose as compared to baseline (p<0.05). Despite the observation that mean values of fasting blood glucose were at the upper limit of normal at the end of the 6-month study and at one year post-intervention, the proportional change is represents favorable reduction in diabetes risk in the subsample at one year post-intervention. Insulin resistance and HbA1c demonstrated favorable proportional change, but failed to reach statistical significance. Low density lipoprotein increased slightly in the sample (4%), which could be due to a number of unknown influences, particularly factors related to dietary composition or genetic predisposition.
Frequency tables suggested a trend toward risk reduction in the subsample for every marker except LDL. Insulin resistance ratio (triglycerides/HDL) was normal in 34 participants at one year (71%) compared to 28 at baseline (58%). Blood glucose was normal for 36 (75%) participants at one year as compared to 31 (65%) at baseline. And finally, HbA1c was normal in 38 (79%) participants one year post-intervention as compared to 33 (69%) at baseline. Of note, the one year post-intervention analyses was powered to detect significant changes in weight, not risk markers, therefore these findings may not reflect changes representative of all technology-enabled participants. Despite this, the empirical findings suggest a favorable change in cardiovascular and metabolic disease risk in the sample population one year post-intervention.

This study attempted to identify predictors of risk reduction using single and multiple regression modeling. Current physical activity was found to be a predictor of insulin resistance both in the linear regression model and the multiple model (p =0.02 and 0.03, respectively). This finding is consistent with well-established research that has demonstrated that even moderate decreases in weight can result in metabolic disease risk reduction (Wing, et al., 2011; Van Gaal, Mertens, & Ballaux, 2005; Blackburn, 1995). In addition, the finding supports evidence from the Diabetes Prevention Program (Kriska, et al., 2006) that characterizes regular physical activity as a powerful prevention strategy against the onset of diabetes.

In terms of changes in cardiovascular risk, the frequency tabulations revealed a slight increase in LDL in females in the one year post-intervention sample. At one year
post-intervention, 20 females in the sample had normal LDL levels (below 130 mg/dl) compared to 24 at enrollment. Despite moderate weight loss and increased physical activity, cardiovascular disease risk effectively increased in this group. This underscores the need to closely monitor risk status and employ alternate strategies for risk reduction as needed.

**Public Health Implications**

Interactive web-based technology is increasingly playing a role in all aspects of life, including health improvement interventions such as weight loss. Today, individuals can map a walking route, track blood pressure, or communicate with friends and family with minimal interaction with a home computer, tablet or smart phone. The very nature of today’s web-oriented world allows for rapid, widespread connection across a variety of environments, such as the workplace, clinical environments and the public health sector. For health improvement interventions like weight loss, interactive technology may provide an alternate means to accelerate the efforts against the raging epidemic of obesity. In doing so, it will be imperative to understand the effectiveness of interactive technology, the underlying mechanisms of use, and associated outcomes. In that regard, the present study provided several important insights into technology-enabled weight loss approaches.

The 6-month iWell randomized clinical trial tested an interactive technology approach against a self-directed approach in a health improvement and weight loss intervention in adult healthcare workers. Using wireless transmittal tracking instruments
and an interactive website (including a dedicated OSN), results demonstrated significant weight loss outcomes for the technology-enabled participants compared to the self-directed group. The present study attempted to identify predictors of success in the technology-enabled participants who completed the 6-month iWell study (n=168) and a subsample of that group (n=48) at one year post-intervention, examining factors associated with short and longer-term outcomes. A main focus was to determine if aspects of this approach could be used to inform design of future health improvement and weight loss interventions. The findings of this study indicate that technology can facilitate weight loss through the use of integrated tracking features and to a lesser degree, online social networking. In addition, outcomes in a subsample of intervention participants one year post-intervention show evidence of successful weight loss maintenance and metabolic disease risk reduction. Although there are important limitations to consider when synthesizing the results, this preliminary assessment of an innovative health improvement strategy suggests that the framework of technology combined with social networking can have a positive impact on health, with particular regard to weight loss.

In the iWell clinical trial, all intervention participants were given wireless instruments and were connected to a designated online social network to facilitate health improvement and motivate behaviors that would result in weight loss for the duration of the 6-month trial. They could view their own progress and biometrics, and communicate with other intervention participants via the iWell website, throughout the study period. Given equal access, use of the technology features (activity uploaded, weight uploads,
use of the OSN) varied, as did subsequent weight loss. A key finding of the study was that participants who tracked weight and activity more were more likely to demonstrate significant weight loss as compared to those that utilized the tracking tools less. This has important implications for future study designs, as it demonstrated that self-monitoring of weight and activity through selected technology tools was effective for weight loss.

Implications of results related to using the online social network feature are less clear. Overall utilization was sub-optimal in this cohort. On average participants used the OSN a total of 11.2 times during the 6 months. This could be due to unfamiliarity with OSNs, concerns with privacy or other unknown factors influencing engagement. The fact that the using the OSN required more time than using the other technology features may have inhibited overall utilization. Using this feature was different than using the tracking tools which required simple and instantaneous transmittal of data. Like using any other OSNs, requesting and maintaining connections, and communication in general, takes time and could present a barrier to engagement. Social support has been long associated with health improvement (Uchino, 2004; Cohen, 2004) and the iWell OSN was intended to provide this among a group of people who were pursuing a common goal. The reasons for underutilization of the iWell OSN are not known. Future research efforts are necessary to better understand the effectiveness of OSNs, and to explore the mechanisms behind the use of technology features, including motivational factors and identification of barriers to engagement.
The translation of findings from this study and previous studies focused on technology-enabled weight loss will require concerted efforts to keep pace with the evolving technology, where “state-of-the-art” can become obsolete in a matter of just a few years. How people access and use technology as a support for behavior change will require additional and on-going research. Functionality of websites, device options and communication methods continue to rapidly advance. Intervention designs that incorporate interactive technology will need to evolve alongside technology to have the greatest impact on population health. Mobile technology is literally in the hands of the majority of U.S. adults (Smith, 2013) and is becoming the standard globally as well. This presents additional opportunities for development of interventions that can be used with mobile devices, allowing users to engage in health monitoring and management virtually anytime and anyplace. With this in mind, it will be imperative for public health professionals to collaborate with technical experts in the design and implementation of effective technology-enabled interventions.

The applications of findings of this study provide a framework for the integration of technology features in weight loss interventions. This relatively new approach, combining interactive technology with social support, may work well with certain populations, but clearly would benefit from refinements to improve effectiveness. Results indicate that a target population such as healthcare workers can lose weight and improve health using a technology-based platform, even when utilization of certain technology features is sub-optimal (the online social network). Despite this, the findings suggest that technology-enabled approaches can result in modest but health-beneficial
weight loss and reduced cardiovascular and metabolic disease risk, in the short and longer term. With appropriate revisions to the study design and methodologies, this approach may be viable for environments with similar technology infrastructures (worksites, schools, government or clinical agencies).

In the present obesogenic environment, the need for novel and effective weight loss strategies is urgent. Technology is permeating every aspect of modern living, conferring benefits of convenience, cost effectiveness, and scalability that have not been seen previously. Today, with the majority of Americans “wired,” it may be possible to engage the masses in ways that are appropriate, interesting, and utilize scientifically defensible behavioral strategies that are likely to motivate change. More research is needed to explore exactly why participants did not utilize technology as expected, and what it would take to engage them more actively in various technology-oriented study components. Efforts to improve population health, particularly weight loss maintenance efforts should recognize the advantages of using selected technology features, with intervention designs that have been carefully refined to target appropriate populations, with optimal use of technology elements, for specific health improvement outcomes.

**Limitations**

This research yielded several important insights as to how technology can be used to improve weight loss efforts and improve health. However, a number of important limitations may have impacted the quality of the findings and the ability to thoroughly answer each research question.
In terms of methodological limitations, there are several limitations related to sampling. First, participants in the 6-month intervention were recruited from the healthcare organization worksite, creating a possible self-selection bias and a sample that may have contained people with a greater interest in health, as compared to a truly randomized sample. The iWell study participants were healthcare workers—a population assumed to be healthier to begin with (Lemon, et al., 2010). Participant motivation and other possible variables may not be representative of the general population.

Secondly, the sample sizes for both the 6-month study (n=168) and the one year post-intervention subsample (n=48) may have been too small to determine significant relationships between potential predictor variables and the primary outcome of interest, weight loss. For the 6-month study, retention rates were adequate but could have been better. Sixty-six percent of intervention participants completed the study (n=168). This rate may have been affected by the lack of appropriate strategies to optimize retention. Incentives were given to participants at the 3 month assessment (cookbook) and the 6-month assessment ($15 gift card). These may not have been adequate to ensure full participation. As for the one year post-intervention subsample, a number of factors may have limited participation. Intervention participants were contacted via email addresses used during the 6-month study. Addresses may have changed in the period between study completion and one year post-intervention. It is also possible that a number of participants were lost to follow up due relocation or work re-assignment. Unlike the 6-month study, there were no incentives offered for participation. Larger sample sizes with better retention rates in future studies would help ensure representative distribution of the
population under study, and would make the results more generalizable to adult populations wishing to improve health and lose weight. Future studies should have strategies in place to optimize retention and to maintain contact with study participants beyond the study period, especially if additional follow up is a consideration.

A third limitation involves the lack of existing comparable studies. Although this study included components of technology that have been used before, the specific technology platform has not been tested previously. This inhibits the ability to make comparisons between outcomes of this study and previous work involving technology-enabled weight loss. This is a limitation noted across the spectrum of technology-enabled interventions, where integrated features and components differ, making true comparisons nearly impossible. The understanding of how interactive technology impacts weight loss efforts would benefit from replicated studies that use similar frameworks, components and intervention designs.

Additionally, the measures used to collect data for the one year post-intervention analysis may have limited the ability to interpret longer term outcomes. Specifically, the one year post-intervention assessment was added to the study protocol after the study ended, and was comprised of 48 participants who completed the optional follow-up assessments. Limited funding was available for the operational aspects (staffing and lab analyses) of data collection therefore no incentive was offered for participation. Although the overall response rate was adequate (41% of the 168 intervention participants responded to the invitation) the study was powered for a sample size of 48,
and once this was reached, the assessment period ended. These 48 participants may have been more engaged to begin with or more motivated than other participants in the 6-month study and therefore may not have been representative of the technology-enabled group as a whole. This methodological limitation could be avoided by either designing a longer intervention period, or including post-intervention assessments in the study protocol. Consideration should also be given to funding post-intervention data collection efforts, including the provision of an incentive for participation.

Lastly, some of the data gathered at one year post-intervention was not gathered at any other time point, making comparisons difficult. The nature of some of the data was qualitative, in contrast to purely quantitative data used to analyze 6-month outcomes. For instance, participants in the subsample were asked to rate perceptions of health at the one year post-intervention time point only, making it difficult to draw conclusions about responses, since they were not asked about health perceptions at any other point. The same is true for responses pertaining to perceptions of benefit from participation in the study. This type of data was not collected prior to one year post-intervention therefore the overall meaning of responses to these questions is questionable. With regard to the one year post-intervention data, information about current activity habits, weighing frequency and use of online social networking was self-reported. This method of data collection is subject to both over-reporting and under-reporting and should be considered when interpreting results.
Suggestions for Future Research

This study was a preliminary examination of a new approach to health improvement and weight loss using interactive technology and online social networking. In general, the results indicate the format of social support coupled with interactive technology may be effective for short and longer term weight loss and health improvement with certain populations. Given some of the limitations of the present study, this approach needs to demonstrate greater effectiveness before being used with other populations. Key refinements related to intervention duration, technology utilization, weight assessment measures, education regarding health risks associated with overweight and obesity, dietary modification and overall sampling procedures will likely improve the effectiveness of technology-based approaches and the ability to target specific populations.

Since results from this study and others have found weight loss to be achievable in the short-term, future studies should consider longer intervention periods, where participants could use activity and weight tracking features over an extended period of time. The iWell intervention was 6 months in duration and may not have been long enough to detect more significant health indicator changes had the participants used the technology features and iWell portal for a longer period of time. A longer, supported intervention period beyond 6-months may provide greater insights related to technology use and sustained weight loss. Ideally, such a design would include strategies to retain participants (incentives, rewards, in-person contact) and encourage continued use of
technology features. A longer duration intervention may be prone to higher attrition, but with appropriate sampling procedures and on-going support the results may yield important insights involving factors influencing what has been largely elusive to researchers thus far—weight loss sustained over time.

Technology-enabled interventions should include measures to pair appropriate technology with appropriate populations. User preferences should be taken into consideration with respect to devices that are used, methods of delivery (mobile or desktop), and website design and navigation to ensure engagement, especially in the early stages of the intervention. In other words, as part of the intervention design and data collection, technology use should be carefully monitored and intervened with as necessary, with strategies in place to encourage and support early adoption and continual use of these features throughout the intervention. These strategies might include incentives for use, electronic “nudges” via email messages, and timely, accessible technical assistance. Instructional strategies appropriate to the target population should also be in place to assist those who may require more education or training related to use of the technology system and components. To better understand factors related to on-going use, technology use should be measured at regular intervals throughout the study period, including passive engagement (viewing) as well as active engagement (device uploads, posting on the online social network). In addition, feedback from users—including satisfaction scores—should be collected to analyze and better understand user preferences.
In analyzing Framingham data, Christakis and Fowler (2007) determined that obesity could be “spread” through a social network. As they postulated, when people are connected, their health is connected. Using this same logic, it would follow that wellness could be “spread” through a social network. For future technology-enabled weight loss interventions, this theme should guide the design and implementation of the project, to ensure better utilization rates. The OSN component should be highlighted when recruiting, enrolling and training study participants, emphasizing the connection between social support and successful weight loss. This would allow for closer examination of relationships between OSN use and weight loss outcomes. Results of the present analyses may have differed if utilization rates of the iWell OSN were greater. Reasons for low utilization are not known, but may have been due to unfamiliarity with OSN’s, concerns about privacy, general disinterest, or time constraints. These factors were not assessed in the technology-enabled participants at baseline, and the social support aspect of this feature may not have been apparent (or of interest) to participants. In addition, the OSN may have been used passively (primarily for viewing communications) rather than actively (sending messages, posting, commenting) by participants. These issues may have influenced assessments of use, and engagement in general. Future studies should consider assessing attitudes and behaviors related to technology use, including OSNs, to ensure optimal engagement. In addition, consideration should also be given to making technology features of the intervention (including the OSN) compatible with mobile computing, as an alternate to desktop computing, given the ubiquity of smartphone use and ownership.
Future studies may also consider a combined technology and personal contact approach to retain participation and improve longer term outcomes. The iWell study was highly automated with minimal in-person contact. After an in-person enrollment session, participants met face-to-face with a clinician or study investigator only during assessments or follow-up with a primary care provider. Previous studies have suggested that interventions with occasional in-person contact may lead to greater retention rates and improved outcomes (Neve, Morgan, Jones, & Collins, 2010; Webb, Joseph, Yardley, & Michie, 2010). Although such approaches may be more costly, the improved longer term outcomes may justify the additional expense.

In the design of future weight loss interventions, investigators may consider using alternate measures of weight, avoiding inherent problems associated with using BMI as the sole indicator of healthy weight. Although BMI is conveniently measured in the general population, it fails to account for fat distribution, particularly abdominal adiposity. Using alternate measures to assess fat distribution (dual energy x-ray absorptiometry, waist circumference, waist to hip ratio) may more accurately detect body composition changes that are of practical importance.

The relationship of diet to weight loss outcomes should be explored in future technology-enabled interventions, by including a diet tracker similar to the activity and weight trackers that were used in the iWell study, and were associated with more favorable outcomes. The iWell intervention did not include a structured dietary component and no dietary data was collected, despite a multi-component technology
platform. The interactive tools used by the technology-enabled group enabled tracking of physical activity, weight and lab values, and in the subsample, these tools were perceived as having a positive impact on health. Integrating a technology feature to track dietary data could provide further insights regarding technology-enabled weight loss. Ideally, this type of feature would be integrated into the website system, with the same efficiency and feedback mechanisms used for tracking weight and activity.

Nearly 80% of the iWell participants were English-speaking, Caucasian women over the age of 50. For this reason, it is not known whether this approach would work with other populations. The effectiveness of technology-enabled weight loss interventions should be explored in minority populations, considering the known disparity in overweight and obesity prevalence in minority populations (Ogden, Lamb, Carroll, & Flegal, 2010; Wang & Beydoun, 2007). Minority populations including Hispanics and African Americans have some of the highest rates of obesity (CDC, 2012) but also have some of the lowest rates of home internet use, relying more on mobile technology (smartphones, tablets) as compared to whites (Zickurh & Smith, 2012; Christopher-Gibbons, 2011). Therefore future studies should examine the cultural relevancy of technology-enabled approaches to address overweight and obesity in minority populations.

**Conclusions**

Overweight and obesity will remain leading health issues until effective, long-term interventions are in place. This is a challenge that public health professionals can
(and should) lead. Embracing well-designed, cost-effective and scalable approaches that incorporate technology features may be one way to de-escalate the rising prevalence of obesity.

The present found that instrumenting a given population (healthcare workers) with interactive technology tools to monitor weight and activity could impact health favorably, for those that had higher engagement patterns than those that used the technology to a lesser degree. In essence, for this population, greater utilization of the technology features resulted in greater weight loss regardless of age or baseline disease burden. Providing an online support system for the studied population conferred less significant benefit, with lower than anticipated utilization. However, using the OSN appeared to exert some degree of influence on weight loss outcomes in men, as those that used it more, lost more weight. In the longer term, the findings indicate weight loss maintenance was achieved by participants in the subsample, as measured one year post-intervention. This finding is of particular significance, as a majority of weight loss studies fail to demonstrate weight loss maintenance in the longer term. In addition, metabolic disease risk was reduced in the one year post-intervention subsample, demonstrating that it is possible to ‘move the meter’, but it may take more time to detect changes in risk markers.

The effectiveness of future technology-based interventions is likely to improve if research designs include assessments of factors related to motivation to use technology, training to ensure proficient, accurate and optimal engagement with technology features,
and education related to obesity-related health markers, personal risk status and prevention strategies. With appropriate refinements, technology-enabled approaches could prove to be effective for population-based interventions that are inherently scalable, cost-effective and convenient. Such approaches have been capitalized on by the private business sector as evidenced by the ever-evolving variety of tracking tools, mobile devices and applications, primarily aimed for individual use.

The learning curve for using interactive technology is becoming less steep for today’s typical user, due to the ubiquitous nature of mobile and desktop applications used for everyday tasks. With respect to using technology for population health improvement efforts like weight loss, determining what works for which outcomes and for whom is proving to be an iterative process for public health professionals. As noted with the ill-fated technology-based Boston million pound weight loss challenge (less than a tenth of the goal was achieved at the end of the challenge), you cannot simply use new tools in old ways and expect different results.

The call to action remains urgent. The current obesity epidemic is a complex societal problem that will require considerable, multi-level efforts to overcome. Incorporating technology into weight loss and weight loss management efforts has the potential to impact obesity prevalence, but technology alone will not solve the problem. Rather, technology-based weight loss interventions must be approached holistically, using design elements and tools that have proven to be effective and considering factors associated with optimal user engagement. Until greater efficacy of technology-enabled
interventions is established, successful weight loss will continue to be more than just a mouse click away.
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