AGE-RELATED DIFFERENCES IN SELF-EFFICACY AND THE USE OF E-HEALTH SUPPORTS FOR EXERCISE BEHAVIOR IN ADULTS

By

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I dedicate this dissertation to my husband, mother and father, family, friends, colleagues and mentors.

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E-Health tools show great promise to promote health because of their broad reach, consistent interventions and reduced cost. Little is still known about the ways in which the public uses these tools, or their perceptions and beliefs about their use. The purpose of this cross sectional study was to describe the electronic health supports used by different age groups, compare efficacy beliefs regarding these tools and to explore the relationship between e-Health support use and social cognitive concepts.

A mailed survey (n = 1,868) was used to gather data from a random sample of participants in a national employer-sponsored wellness program. The age cohorts were Millennials, Generation X, Baby Boomers and Silent Generation. The total weekly minutes of all e-Health tools and e-Health tools to support exercise were significantly different among the cohorts ($X^2(3) = 44.49$, $p < .0001$). Overall as age increased the use of e-Health tools declined. Post hoc comparisons among the cohorts revealed that Millennials utilized e-Health tools more frequently than their older counterparts. Millenials' weekly minutes of e-Health tools was significantly higher than their older counterparts except for Generation X. In addition, the greater number of weekly minutes using e-Health tools was significantly related to greater self-efficacy for e-

Health tool use (r_s = .50, p = .01), while greater e-Health tool use for exercise was significantly related to greater exercise self-efficacy (r_s = .21, p = .0003) and outcome expectations for exercise (r_s = .28, $p \leq$.0001), it was not significantly associated with perceived barriers for exercise (r_s = -.05).

These finding support the existence of age related differences in the use of e-Health tools to support exercise and the relationship between social cognitive concepts and e-Health tools. Consideration of these differences can guide e-Health tool use in different aged groups. E-Health tools should incorporate efficacy-building mechanisms and practitioners should assess e-Health self-efficacy prior to using e-Health interventions. Future e-Health research should explore experiential timing as a factor in e-Health tool adoption, video game use by older adults, tool use for behaviors other than exercise and the effect of multi-component e-Health tools on health behavior.

CHAPTER 1
AGE-RELATED DIFFERENCES IN SELF-EFFICACY AND USE OF E-HEALTH SUPPORTS FOR EXERCISE BEHAVIOR IN ADULTS

Problem and Significance

The United States is on the verge of a health care catastrophe. With healthcare costs spiraling out of control, increased demand and lack of access have put a heavy strain on an already overburdened system. Genetic predisposition and environmental factors notwithstanding, most leading causes of death in the United States posses a lifestyle or behavioral component (Centers for Disease Control [CDC], 2012). Chronic conditions such as obesity, heart disease, hypertension, stroke, some cancers and diabetes are directly related to a sedentary lifestyle (Centers for Disease Control [CDC], 2009; Chodzko-Zajko, Proctor, Singh, Minson, Nigg, & Salem, 2009; Millen & Bray, 2009; Nelson et al., 2007). According to one study, half of all annual deaths in the United States can be attributed to preventable causes that are facilitated by poor health behaviors (Mokdad et al., 2004).

Implementation of primary preventive measures such as routine exercise can dramatically impact the development of diseases and even improve glucose control in diabetics (Resnick, Luisi, Vogel, & Junaleepa, 2004; Song, Ahn, Roberts, Lee, & Ahn, 2009). In addition to impacting disease development and progression, the CDC (2006) reported that medical costs decrease dramatically as physical activity increases. The American College of Sports Medicine (ACSM) states that lack of exercise in adults contributes to poor health, including the development of preventable illness and functional decline (Chodzko-Zajko et al., 2009). In addition, the CDC (2006) reported that over time, participation in regular physical activity declines with age. Recognizing the importance of exercise participation to personal health, both the ACSM and CDC

have issued guidelines for exercise in an effort to decrease mortality and reduce the development of preventable chronic conditions like diabetes and heart disease (CDC, 2006; Chodzko-Zajko et al., 2009).

Technology is ubiquitous and pervasive and the numbers are staggering. For example, the number of mobile devices will outnumber global population by the end of 2012 (Institute of Engineering and Technology, 2011). As of May 2012, there were 900 million users of the online social network *Facebook* with numbers expected to exceed 1 billion by the end of the year (Mashable, 2012). Furthermore, of the 46% of adults who use social networking sites, 11% of them have followed a friend's health updates, 8% used the site to memorialize someone who suffered from a condition and 7% of them have obtained health information there (Fox, 2013). Self-monitoring tool use is also increasing, with 27% of adult Internet users tracking their health data online. Finally, there are currently 40,000 mobile health applications available and 247 million individuals have downloaded at least one to their mobile device (Jahns & Gair, 2012).

Electronic Health (e-health) tools are proposed to extend the reach and efficacy of behavior change interventions across large populations with emerging data supporting their effectiveness (Fukuoka, Kamitani, Bonnet & Lindgren, 2011; Noar & Harrington, 2012). The term e-Health broadly defined references the "Heterogeneous and evolving digital resources and practices that support health and health care" and delineates a burgeoning field of study encompassing multiple disciplines (Office of Disease Prevention and Health Promotion, 2006, p.xi). Moreover, e-Health supports are the specific digital tools used to support health behavior (U.S. Department of Health and Human Services, 2012). Further study is needed to provide theoretical support for the

efficacy of e-Health support use among different aged populations as well as expanding current knowledge of the ideal ways in which these tools should be constructed, tested and deployed.

E-Health tools offer various ways by which an individual can initiate, engage, track and maintain healthy behaviors, including exercise. Interest is mounting to assess the utility and efficacy of electronic devices and supports as means to curb diseases both nationally and abroad (World Health Organization, 2011). Although the use of e-Health is expanding, little evidence exists supporting the efficacy of these tools in driving sustained behavior change. Furthermore, little is known about the patterns of adoption for e-Health supports among different age groups, the reasons why different groups use these supports and whether certain supports are preferred by specific ages. Finally, currently nothing is known about efficacy beliefs for the use of these tools among different aged adults.

Exercise participation and social cognitive constructs have been well studied among different age groups; though few of these studies include the use of electronic tools to support healthy exercise behaviors. E-Health support use may be efficacy building and warrant further study to determine impact on exercise participation. Considering the rapidity with which these emerging technologies are being adopted, and the inherent benefits of exercise participation, understanding how these supports are used by different aged participants can aid in development e-Health tools and interventions to improve health through exercise. E-Health tools are being used more frequently to manage disease, which impacts older adults more frequently, thus

understanding age-related differences will aid in delivering these tools appropriately (Topol, 2012).

Conceptual Framework

Electronic health tools offer ways in which an individual can interact with and receive various types of health related information, thereby helping form beliefs about specific types of health behaviors. Social Cognitive Theory (SCT) is deeply rooted in the study of human learning and behavior. A central concept of the SCT is reciprocal determinism. Humans are in a constant state of interaction with their environment and are affected by it, while at the same time affecting the environment around them (Bandura, 1997; Glanz, Rimer, & Viswanath, 2008; Pajares, 2002). Using e-Health supports can help build positive self-beliefs regarding one's ability to engage in, and maintain healthy exercise behaviors.

Self-Efficacy

Bandura (1997) defines self-efficacy as one's personal belief in their capability to perform an action. Bandura adds, "Perceived self-efficacy is concerned not with the number of skills that you have, but with what you believe you can do with what you have under a variety of circumstances" (1997, p.37). Simply put, how confident a person is in their ability to complete a task, given a variety of stressors. Based on SCT, self-efficacy can be influenced in different ways through the use e-Health supports.

Mastery Experiences

Of the four mechanisms to increase self-efficacy, mastery experiences provide the greatest influence on personal efficacy beliefs (Bandura, 1997). As some experience continued successes with a task, their confidence in their ability to perform increases. Conversely, repeated failures can decrease personal efficacy and will be

detrimental to positive performance. If failures are experienced early in the behavior change process, they will have a greater negative impact than if the individual experiences a setback after some successes. Since mastery experiences provide directly observable evidence of one's capabilities, they are the most influential on self-efficacy beliefs.

Mastery experiences affect performance through cognitive appraisal of that experience (Bandura, 1997). Thus, perception of the effort required completing the task, along with judgments about the ease or complexity of the task and related circumstances would greatly influence how self-efficacy will be affected. For example, success with a task that a person judges to be easy in nature will have less of a positive influence on efficacy belief than success with a complicated or difficult behavior. Moreover, the amount of effort expended or assistance received in performance of the task can influence the degree to which efficacy beliefs are enhanced.

Electronic health supports are uniquely positioned to provide mastery experiences for exercise. For example, many gaming platforms utilize progressive learning techniques that allow the user to move through increasingly difficult stages. As the user becomes more proficient and completes earlier levels, they are presented with more challenging tasks. In this way, electronic games provide opportunities to master tasks, thereby building efficacy beliefs. In another example, websites where users track progress are able to show the user how far they have progressed towards a goal. As they continue the healthy activity, in this case exercise, they are able to visualize their successes on the screen, which reinforces their beliefs that they are capable of continued success.

Vicarious Learning

Another key component of the SCT is the concept of vicarious learning. According to Bandura (1997), human beings learn by observing another's behaviors and are an effective way to influence self-efficacy. Humans tend to emulate those who appear most like us. The more a person observes another similar person completing a task or behaving a certain way, the more likely they are to attempt to repeat that behavior (Bandura, 1986, 1997).

With the advent of online social networks, individuals can now interact with others more easily than ever before. For example, Facebook has over 1 billion users so far and hundreds of different groups related to health and exercise. In addition, many health-specific websites have incorporated social networking as a way to allow like-minded individuals the opportunity to share and interact with one another while attempting a common goal. The *Livestrong* website allows members to join different groups based on that particular group's healthy goal. Thus, members can join the "lose 20 lbs. in 20 weeks" and share with each other thoughts about their successes and failures as well as provide each other support and encouragement. Members can also share their progress with others, providing support for the efficacy beliefs of other members who are working towards the same goal.

Verbal Persuasion

Feedback in the form of verbal communications also has an impact on self-efficacy beliefs (Bandura, 1997). Affirmative statements given to individuals regarding their capabilities support their beliefs that they possess the characteristics needed to be successful in their endeavors. Individuals receiving verbal persuasions regarding their capabilities evaluate the persuasory statement against their beliefs and prior

experiences with the target action. Therefore the effectiveness of verbal persuasions is linked to whether the individual believes the person making the statements and whether they believe that they can actually produce the required outcome.

In addition to social networks impacting efficacy beliefs though vicarious learning, they can also be the source for statements of encouragement from other users. As an individual interacts with others in social networks who share the same goal of improving exercise, they can receive positive supporting statements from other participants. In effect, they “coach” each other through difficult times and provide tips on ways to be successful. These positive supportive statements can improve efficacy beliefs related to exercise participation.

Physical and Emotional States

The fourth and final way to influence self-efficacy beliefs is through the cognitive appraisal of somatic and affective arousal (Bandura, 1997). These physical and emotional indicants impact efficacy beliefs through one’s attributions concerning the sources of the arousal, perceptions of the arousal and the efficaciousness of the individual experiencing the arousal. The influences of somatic indicators are particularly robust when related to health related tasks, coping strategies and physical activities (Bandura, 1997).

Social networks provide opportunities for ongoing support when individuals are experiencing somatic complaints or emotional states. Other members within the group provide positive supportive statements as well as share their own experiences and how they disregarded negative states in order to achieve success. Furthermore, many exercise-based games today provide positive supporting statements while completing the exercise, especially during the most challenging portions.

Outcome Expectations

One of the principal psychological determinants of health behavior is outcome expectations. Expecting a positive result from physical activity has been shown to relate to exercise participation in many studies. Outcome expectations describe how a person feels or believe about a particular consequence of a behavior and the value the individual places on that outcome (Bandura, 1997; Glanz et al., 2008; Pajares, 2002). In addition to individual value judgments about the outcome, a person's behavior is also influenced by the belief that others will view the behavior in a certain way (Bandura, 1997, 2006a; Glanz et al., 2008). Finally, the individual also can be influenced by the expected sense of personal satisfaction achieved when successfully completing the intended behavior (Bandura, 1997, 2006a; Glanz et al., 2008).

The higher a person's expectations about the outcome of task or behavior, the more likely they will engage in and be successful completing it (Bandura, 1986, 1997). For example, if a person believes that their social support views their participation in a particular behavior in a positive way, then the individual will be more likely to engage in it. Also, one may believe that maintaining physical activity levels does not provide any real benefit; therefore they would be less likely to engage in it routinely.

Use of e-Health tools support individuals' outcome expectations for exercise in several different ways. First, as they interact with others who share common values about exercise within in a social networking environment, they are engaging others who may view exercise as important, thereby positively influencing their outcome expectation for exercise. Secondly, they are able to see positive results of exercise from other participants within their social group, thereby influencing their own expectations about results they will receive as well.

Facilitation

The environmental determinants of behavior include incentive motivations and facilitation (Bandura, 1986, 1997; Glanz et al., 2008). Incentive motivations are external rewards or punishments used to direct behavior (Bandura, 1997). For example, providing punishment in the form of laws can have unintended consequences, such as increased smoking in teens rather than a less punitive method such as increasing cigarette costs, which were effective at reducing smoking in teens (Glanz et al., 2008). In addition, facilitation affects behavior through the increase in available resources needed to change behavior (Glanz et al., 2008). For example, facilitation can be achieved through effective identification and removal of barriers that prevent one from making a change (Glanz et al., 2008). As perceived barriers decrease, the likelihood of engaging in a behavior increases.

Self-Regulation

Within the SCT, a person can direct changes in behavior based on the rewards and changes to the environment they provide for themselves (Glanz et al., 2008). This is called self-regulation and is achieved through the following six methods: Self-monitoring, goal-setting, feedback, self-reward, self-instruction and enlisting social supports (Bandura, 1997; 1986; Glanz et al., 2008).

E-Health support use provides ways for the individual to utilize various self-regulatory mechanisms to improve health. Many games, mobile devices and directive websites provide opportunities to set health-related goals as well as providing ongoing feedback on goal attainment. In addition, these sites provide rewards in the form of badges or additional functionality for achieving certain milestones. Also, health related websites often provide self-directed learning opportunities to improve health literacy. As

explained earlier, social networks provide support for individuals who are seeking to change behaviors.

Background

The relationship between exercise and health outcomes has been well studied with similar results pointing to increased exercise and improved health across adult age groups (Anderson-Bill, Winett, Wojcik & Winett, 2011b; Conn, Hafdahl, Brown & Brown, 2008; Dunlap & Barry, 1999; Elavsky, McAuley, Motl, Konopack, Marquez et al., 2005; Telama, Yang, Viikari, Valimaki, Wanne et al., 2005). Also well established is how age group exercise patterns vary. For instance, exercise participation declines with age, even though evidence suggests continued participation improves quality of life, strength, balance, and cognition while promoting independence (Elavsky et al., 2008; Gerling, Schild & Masuch, 2010; Telama et al., 1997).

Social cognitive theory has been utilized frequently as a framework to explain various health behaviors, including exercise behavior in adults (McAuley, Jerome, Marquez, Elavsky & Blissmer, 2003; McAuley, Morris, Motl, Hu, Konopack et al., 2007; Rejeski, Tian, Liao & McDermott, 2008Resnick & Nigg, 2003). While self-efficacy is most often mentioned as a significant predictor of exercise behavior (McAuley et al., 2003; Millen & Bray, 2009; Neupert, Lachman & Whitbourne, 2009), other variables such as outcome expectations (Anderson-Bill, Winett & Wojcik, 2011a; Hortz & Petosa, 2008; Millen & Bray, 2009; Resnick, Luisi, Vogel & Junaleepa, 2004) and perceived barriers to exercise (Daskapan, Tuzun & Eker, 2006; Dunlap & Barry, 1999; Lees, Clark, Nigg & Newman, 2005; Leveille, Cohen-Mansfield & Guralnik, 2003) have also been demonstrated to be influential across age groups. Whether self-efficacy influences exercise to a greater degree than other social cognitive variables is a matter

of some debate. Resnick et al., (2004) found that outcome expectations were more influential than self-efficacy in predicting exercise behavior. While evidence of self-efficacy's influence on behavior has been well documented, no such relationship has been studied between self-efficacy and the use of e-Health supports.

There are age-related differences in the use of various types of technology such as: Internet use (Chu, Mastel-Smith, 2010; Cohall, Nye, Moon-Howard, Kukafka, Dye et al., 2011; McInnes, Gifford, Kazis, & Wagner, 2010; McMillan & Macias, 2008), online health programs (Bickmore, Caruso, Clough-Gorr & Heeren, 2005), social networks (Fukuoka, Bonnet, Lindgren, 2011; Nahm, Resnick & Gaines, 2004), video games (Gerling, Schild & Masuch, 2010; Nitz, Kuys, Isles & Fu, 2010; Pearce, 2008) and self-monitoring devices (Beaudin, Intille & Morris, 2006; Svensson & Lagerros, 2010). While knowledge exists regarding the use of these tools for health related activities by different age groups, too little is known about their use to support exercise behaviors and whether age-related preferences exist in their utilization.

Some suggest how e-health support use may influence social cognitive variables such as self-efficacy (Anderson-Bill et al., 2011a; Bandura, 2004; Song, Peng & Lee, 2011), outcome expectations (Anderson-Bill et al., 2011a; Bandura, 2004) and barriers to exercise (Boschman, 2010; Center for Technology and Aging, 2011). Little is known about how these technologies support social cognitive influences of exercise behavior among adults. Furthermore, a significant gap exists in the exploration of age-related differences between the influence of e-health support use and social cognitive influencers of exercise.

Purpose of the Study

There is little empirical data to support understanding efficacy beliefs regarding the use of e-Health tools by different age groups and whether they are used to guide exercise participation. This research was designed to build on existing knowledge about the use of e-health tools, self-efficacy for their use and exercise behavior across age groups. This purpose of this study was to describe the various electronic health supports used by different age groups, compare efficacy beliefs regarding these tools and to explore the relationship between e-Health support use and social cognitive concepts. Figure 1-1 represents the theoretical framework for this study with accompanying relationships depicted.

Specific Aims

Specific Aim 1

1. To describe age-related differences in the frequency of e-health support use.
    a. Hypothesis 1: E-health support users of different ages will demonstrate differences in the frequency of e-health supports used.

Specific Aim 2

1. To determine if self-efficacy for e-health support use is related to increased utilization of these resources.
    a. Hypothesis 2: A higher level of self-efficacy for e-health support use is related to higher levels of utilization.

Specific Aim 3

1. To determine if e-health support use for exercise increases self-efficacy for exercise, outcomes expectations for exercise and decreases perceived barriers for exercise when used by adults?
    a. Hypothesis 3: E-health support use will be related to greater self-efficacy for exercise.
    b. Hypothesis 4: E-health support use will be related to greater outcome expectations for exercise.

c. Hypothesis 5: E-health support use will be related to decreased perceived barriers for exercise.

Summary

The proliferation of various diseases largely attributable to lifestyle influences such as lack of exercise remains an important problem in the United States. With two thirds of the entire U.S. population overweight or obese (CDC, 2011), it is becoming imperative to find solutions to address obesity and its associated sequelae. Behaviors such as poor eating habits and inactivity contribute to the epidemic of obesity and subsequent chronic disease and can often be treated or mitigated through healthy lifestyle changes. Simply maintaining a routine exercise program can drastically improve morbidity and mortality. Unfortunately, many do not maintain activity levels needed to prevent illness and promote health with significant decreases in exercise as we age.

The benefits associated with routine exercise have been widely studied across populations with several theoretical perspectives demonstrating associations with sustained engagement in exercise behavior. Self-efficacy has also been examined using various theoretical perspectives and is overwhelmingly influential in driving actual behavior. The more efficacious the individual, the more likely they are to engage in the activity about which they feel most confident. In addition, perceived barriers, goals and expected outcomes have been repeatedly shown to influence exercise.

Electronic media use has grown with the ubiquity of home computers, gaming consoles, broadband and wireless Internet connections as well as mobile devices. Unfortunately the problem of sedentary lifestyles has often been attributed to various forms of media consumption since they historically were torpid activities. Now with social exercise networks, exercise gaming, online fitness programs and self-monitoring

tools, the use of electronic media may be transformed into a health benefit rather than a risk. This research is intended to expand current understanding of self-efficacy as described in social cognitive theory in relation to e-health support use, how different age groups use these technologies and how their use relates to known social cognitive influencers of exercise behavior.

Definition of Key Terms

Exercise. Physical activity is any skeletal muscle driven movement that increases energy expenditure. By contrast, exercise is defined as planned purposeful movements conducted with the intent of improving or maintaining physical fitness. Moderate activity is defined as purposeful movement with increased effort and can include activities such as brisk walking, swimming or light cycling while vigorous exercise includes jogging, cycling at a faster pace and cardio respiratory fitness (Thompson, Buchner, Pina, Balady & Williams et al., 2003).

Self-Efficacy for Exercise. A personal belief or confidence in one's capabilities to engage in routine exercise (Bandura, 2004; White et al., 2011).

Outcome Expectations for Exercise. An individual's perceived or expected result of participating in exercise and its relative importance (Millen & Bray, 2009; Resnick & Nigg, 2003; Umstattd, & Hallam, 2007).

Barriers for Exercise. Exercise barriers are defined as perceived feelings, environments, conditions or situations that inhibit participation in regular exercise (Resnick et al., 2004).

e-Health Supports. Forms of electronic media that provide information, directions, connections with others or entertainment and are categorized into the following groups based on how they are used support exercise.

Internet programs. Structured programs with specific instructions to follow in order to achieve a fitness goal and accessed through the web or mobile device.

Social Networks. Websites, programs or mobile applications where individuals can communicate, share information and connect with others.

Self-Monitoring. Methods for tracking various exercise behaviors through the use of pedometers, GPS mobile devices and fitness applications which gather exercise information for display and/or storage by the user.

Exergaming/Exertive games. Mobile, computer or console-based electronic games where users must use exertive interfaces resulting in increased energy expenditure above normal resting energy expenditure.

Self-Efficacy for e-Health Supports. Self-efficacy, in general, is a personal belief or confidence in one's capabilities to complete a particular behavior (Bandura, 1997). Thus, self-efficacy for e-health support use is an individual's belief in their capability to utilize these tools to support exercise behavior.

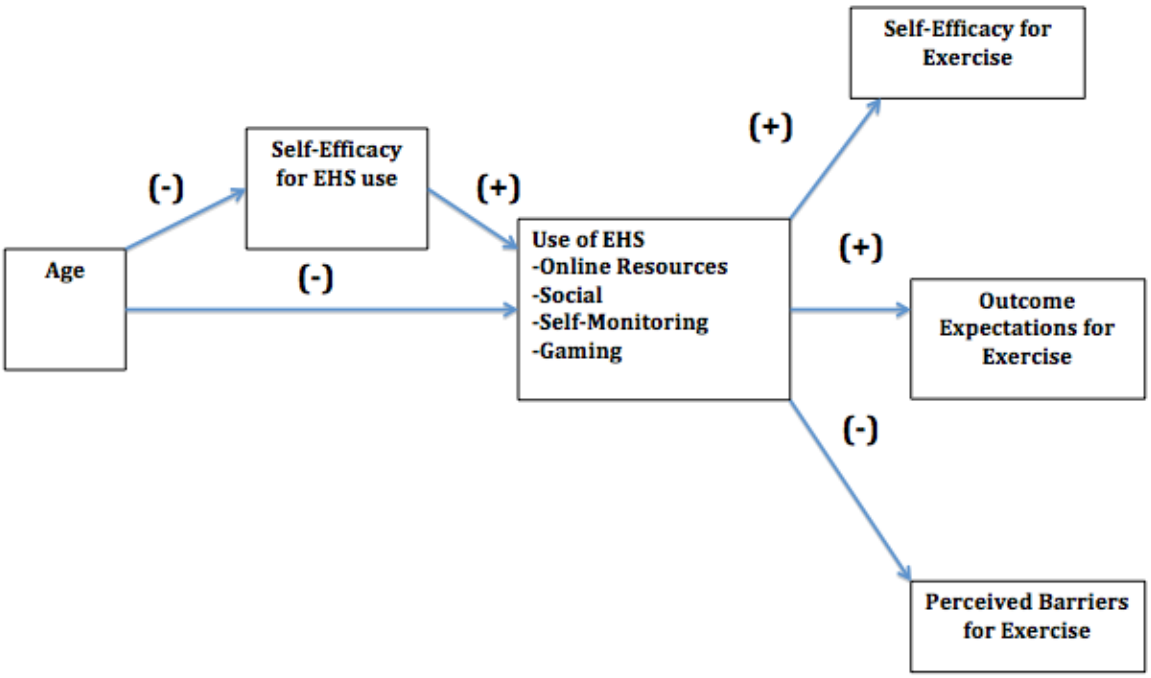

Figure 1-1. Theoretical Framework for Study

CHAPTER 2
REVIEW OF RELATED LITERATURE

Social Cognitive Concepts and Exercise

The literature review begins with an overview of how social cognitive concepts influence various health promoting behaviors, including exercise behavior. Next, the focus turns to e-health support patterns of adoption among different age groups and how they can influence behavior. Finally, e-Health supports are explored for clues on their potential influence on self-efficacy.

Social cognitive concepts and their relationship have been well studied in the context of exercise, with most focusing frequently on exercise self-efficacy. Exercise self-efficacy significantly increases exercise behaviors in adults of all ages (McAuley et al., 2007; McAuley et al., 2003; Rejeski et al., 2008; Resnick & Nigg, 2003). In persons with peripheral artery disease, exercise was explained by exercise self-efficacy and was increased when pain acceptance, satisfaction with function, perceived control and desire for functional competence were added (Rejeski et al., 2008). In a randomized trial of strength training, Neupert, Lachmnan and Whitbourne (2009) found that exercise self-efficacy beliefs were significantly associated with continued participation in strength training for 9 to 12 months post intervention. Thus, increased exercise self-efficacy positively influences exercise behavior.

The influence of self-efficacy on exercise is not without some debate. Hortz and Petosa (2008) examined a self-efficacy intervention's impact and the mediating effects of Social Cognitive Theory (SCT) variables on moderate exercise participation. Social cognitive factors included self-regulation, social situation, outcome expectancy values and self-efficacy. The self-efficacy intervention included instruction on identification and

overcoming of barriers to exercise but did not include interventions based on mastery experiences, social modeling, improving physical/emotional states and verbal persuasion, which are efficacy increasing components in Social Cognitive Theory (Bandura, 1997; Glanz, Rimer, & Viswanath, 2008). While the intervention did not improve self-efficacy and exercise behavior, improvements in self-regulation and social situations were significant and were in included in subsequent meditational analysis. Sobel and Goodman pathway tests revealed that social situation and self-regulation mediated the effects of the intervention on moderate intensity exercise.

In addition to self-efficacy, outcome expectations for exercise have been linked to exercise participation. An individual's expected outcome from exercise participation is related to maintenance of exercise behaviors though its influence is mixed (Anderson-Bill et al., 2011a; Marks & Allegrante, 2005; McAuley et al., 2003, 2007; Resnick et al., 2007; White, Wojcicki & McAuley, 2011). For instance, in a cross-sectional study, structural equation modeling revealed significant but small negative direct effects of outcome expectations on physical activity (β_{direct} = -.14, p = .02), which was somewhat offset by a small, positive indirect effect ($\beta_{indirect}$ = .03, p = .06) and significantly partially mediated (β_{total} = .11, p = .007) through outcome expectations on self-regulation (Anderson-Bill et al., 2011a). By comparison, significant relationships between physical outcome expectations and physical activity (β = .23, p < .05) have been found. In addition, more efficacious individuals have significantly higher physical outcome expectations (β = .22), self-evaluative outcome expectations (β = .26), social outcome expectations (β = .19), goals (β = .27), fewer disability limitations (β = .26), and participate in greater levels of physical activity (β = .27) (White et al., 2011).

Barriers to exercise have been identified as influencing exercise behavior in young adults (Daskapan, Tuzun & Eker, 2006), adults (Murray, Rodgers & Fraser, 2011) and older adults (Dunlap & Barry, 1999; Resnick, Luisi & Vogel; 2008; Zizzi et al., 2006). Perceived exercise barriers can take different forms and are often dependent on age, cognitive ability, disease burden and environment. Exercise barriers in younger adults include a lack of energy, motivation, self-confidence, resources, social support and time (Daskapan et al., 2006) while pain, fear of injury, social isolation, weather and safe environment are barriers for older adults (Leveille, Cohen-Mansfield & Guralnik, 2003).

According to Neupert, Lachman and Whitbourne (2009), environmental barriers and exercise-related barriers are important considerations in older populations because age-related changes like limitations in mobility or cognition can impact the ability to exercise safely. In one cross sectional study of Canadian adults, personal constraints and exercise scheduling self-efficacy mediated the relationship between exercise behavior and subjective socioeconomic status and income (Murray, Rodgers & Fraser, 2011). In addition, while not having enough time to exercise is a significant barrier in other studies (Daskapan et al., 2006), it was insignificant in Appalachian older adults (Zizzi et al., 2006). This inconsistency may be accounted for due to the differences in the ages of the study populations and that fact that one study included college students who may perceive greater demands on their time while engaged in an academic program.

E-Health Resources and Age-related Differences

Age Cohorts

The lexicon of social science commonly includes the definition of different age cohorts as generational groups, though this practice isn't always correct (Ryder, 1965). Labeling groups with similar characteristics such as age is common in social research, especially when attempting to discern differences or make comparisons, though care must be taken not to infer a familial relationship within a group as the term "generation" does. Using the term age cohort or age related group communicates the logical grouping by age without ambiguity. Birth cohorts possess characteristics unique to their group, which are often a product of shared experiences, or social and environmental influences. Consider that age cohorts' temporal experiences will be similar to others within their group and that these experiences shape how a particular cohort views their world. It is often these cluster characteristics that are of interest to science.

Cohort size can impact individual perspectives (Ryder, 1965). For example, baby boomers outnumbered previous cohorts so they had different experiences finding housing, employment and class sizes. Unfortunately, classifying age groups with discrete age ranges oversimplifies the heterogeneity of any cohort. While larger social or cultural experiences influence the beliefs and perspectives of a cohort, individual differentiations between gender, faith, education experience, income and status cannot be overlooked. Indeed, social researchers agree that cohort effects along with life cycle effects and period effects all influence how individual beliefs and perspectives are shaped within a cohort (Pew Research Center, 2010). In addition, while there may be very little difference between a 30-year-old Generation X and a 29-year-old Millennial, some age cutoff is necessary in order to group by age. As long these individual variant

influences are understood in any cohort, valuable information may still be gained by using age groups in research.

Despite several limitations using discrete age groups to compare cohorts in social science research, there are numerous benefits that make these classifications worthwhile. Using commonly accepted nomenclature to group and define age cohorts allows for comparisons across differing studies, thereby creating a more comprehensive description of each cohort's characteristics (Ryder, 1965). In addition, societal acceptance of naming and grouping of different cohorts can add to the broader understanding of these groups beyond the scientific community. For purposes of this research, the terms "age-related group" and "age cohort" will be used interchangeably while the term "generation" will be discarded.

Age-related Differences Affecting Technology Use

The use of e-health tools represents an opportunity to support the health behaviors of older adults, thereby improving quality of life and perhaps extending periods of independence, though little has been done to empirically test this. Older adults are using e-Health tools with increasing frequency (Entertainment Software Association, 2011; Fox, 2010; Gerling et al., 2010; Pew Research Center, 2010) and over half adults aged 65 or older would be willing to use wireless health monitoring devices in their home (Barrett, 2011). Nevertheless, even though older consumer demand exists, developers must consider age-related changes in the creation of e-Health tools so they can be more easily adopted. The ensuing discussion of age-related changes will focus on those normal alterations likely to affect interaction with e-Health tools and is not meant to imply that they are an obligatory component of aging. Indeed,

some individual's age without experiencing declinations explicated here and the distinction should be made between normal aging patterns and pathological ones.

Physical

Physical frailty in aging is associated with increased weakness, loss of endurance, mobility limitations and loss of balance (Ham, Sloane, Warshaw, Bernard & Flaherty, 2007). As physical activity declines and muscle disuse sets in, significant losses of strength occur. Loss of range of motion coupled with decreased bone mass and loss of balance increase both the frequency and severity of falls in older adults. In fact, fear of falling is a primary concern in older adults and moderates feelings of self-efficacy and activity levels in this population (Deshpande et al., 2008). Musculoskeletal changes also include osteoarthritic changes limiting range of motion and increasing pain upon activity. Routine physical activity declines as we age (Nelson et al., 2007), though physical limitations can be improved with routine exercise, thereby reducing the risk of falls through improved gait, strength and stability (Ham et al., 2007).

Age-related changes in vision impact how older adults interact with their environment. These changes are of great importance to e-Health research since many of these tools are visually based. As we age, the lens of the eye loses its ability to accommodate or change shape so that moving a focal point from far to near or vice versa takes longer or requires corrective lenses (Ham et al., 2007). Age-related ocular structural changes (changes in lens shape and size of the iris) limit the amount of light entering the eye thereby decreasing visual acuity. In addition, retinal neural attrition decreases the amount of visual information received and processed by the brain (Morrell, 2001). These changes, including the loss of the ability to discern details or contrast (Crassini, Brown & Bowman, 1988) and color discrimination (Haegerstrom-

Portnoy, Schneck, & Brabyn, 1999), coupled with increased sensitivity to glare, makes it difficult for older adults to read and visualize certain types of information (Echt, Morrell & Park, 1998).

Changes in cognition associated with aging results in decreased ability to perform mental operations such as simultaneously remembering and incorporating new information, multitasking and comprehending text (Craik & Salthouse, 2000). These cognitive changes can begin in early-adulthood (Salthouse, 2004). Evidence points to a typical linear cognitive decline in how new information is stored (encoding), how quickly information is processed and spatial awareness (Hedden & Gabrieli, 2004). Other age-related physiological changes impacting cognition include: reduced cerebral grey matter and neural demyelination resulting in slowed motor response and reaction time and should be considered when designing user interfaces for older adults (Kochunov et al., 2007).

Environmental

Numerous environmental factors that influence technology adoption are not limited to older adults, though they may experience them more frequently. Environmental access to technology is a function of infrastructure (availability) and resources (affordability). The digital divide refers to the limitations of some populations to receive digital services through reduced access or affordability (Kreps & Neuhauser, 2010; Noar & Harrington, 2012). As mentioned previously, many older adults live on fixed incomes and therefore may not be able to afford computers, Internet access, video games or mobile devices. According to Zickuhr and Smith (2012), one in five adults do not have access to the Internet with older adults, those of lower socioeconomic status, Spanish speakers and less educated adults leading this group.

Social

Older adults tend to be educated with about 34% having graduated high school, while by 2030 that number is expected to reach 86% (American Psychological Association [APA], 2012). Many older adults live on fixed incomes derived primarily from social security benefits though 13% live in poverty, compared to 15% aged less than 65. A lack of financial independence can affect the personality and individual dignity of older adults and can restrict autonomous decisions thereby forcing compromises on commonplace activities and precipitating startling role reversals between themselves and their children (Sijuwade, 2009).

Social interaction often occurs in religious meetings with 50% of older adults participating in weekly services (APA, 2012). Also, older adults tend to remain politically active when compared to their younger counterparts. The desire to maintain independence, social interactions and family connections is important to older adults and they turn to technology for this purpose over any other (Barrett, 2011; Burnett, Mitzner, Charness & Rogers, 2011). Two-thirds of adults aged 65 and over use computers to maintain communication with family and friends, representing an increase of 36% since 2007.

While both Millienials (24%) and Generation X (12%) viewed their use of technology as the defining characteristic of their respective generations, Baby Boomers cited work ethic (17%) and the Silent Generation cited the depression and World War II (14%) as theirs (Pew Research Center, 2010). These viewpoints are not surprising when one considers the emergence of various technologies and the differences when they were first experienced and adopted.

Computer technology has existed since the late 1930's though most individuals would not see or interact with these machines until much later. Prior to 1976, computers were often large, bulky devices that could not be used in the home (Computer History Museum, 2006). It wasn't until the advent of the personal computer in 1977 with the Apple II, the first widely adopted personal computer, that exposure to computers became widespread. From that point forward, working environments changed as businesses began to install and use these devices on a large scale. Baby boomers and Silent Generation would have already entered the workforce, which for many, would be their first exposure to these devices. By 1982, Commodore would sell 22 million units of its Commodore 64 home computers, thereby extending the reach of exposure beyond the business environment to millions of homes across the U.S. Currently, the availability of computer technology and the expansion of the Internet has allowed unfettered access to online computer programs, information and social networking capabilities.

In the early 1970's and 1980's home video game systems grew in popularity (Computer History Museum, 2006). Prior to that period, most video games were not commercially available to the general public. Atari created the first widely adopted home video game system with Pong, a tennis-like game played on a television with hand-held controllers. Generation X would have been exposed to home video game systems early in their childhood if their Baby Boomer parents provided them. Most Baby Boomers and Silent Generation members would have purchased these games as gifts for their Generation X children and Millennial grandchildren, thereby shaping their early thoughts about these systems. With the proliferation of arcades in the 1980's, the association of video games as a pleasant, social experience was made by many youth.

This trend continued until the mid to late 1980's, when newer, more advanced home systems allowed home video game playing to overtake arcade gaming.

Patterns of exposure to the Internet by different generations are similar to the exposure to computers in general. First exposure to the Internet for Baby Boomers and Generation X would have likely been in the work environment, while at the same time the Silent Generation and Millennials would have likely used the Internet first at home. While communication between computers existed since the late 1960's, what would become known as the Internet didn't emerge until 1992 (Smithsonian, 2011). From that point forward, companies like Microsoft and America Online opened the door to online information through the creation of Internet browsers and information portals. It wasn't until web browsers and modem connections appeared in personal computers that Internet access in the home became common. As the number of websites grew, it became necessary to access that information in a user friendly way. This was accomplished through the creation of search engines, which allowed users to search for information using key terms and phrases.

Patterns of Adoption by Adults

Adults in each age group use e-health tools on a routine basis, though age-related differences exist in how often and which types are preferred. While younger adults view themselves as being defined by technology, older adults do not (Pew Research Center, 2010). Nearly 90% of younger adults use the Internet, compared to 79% of middle-aged adults and 40% of older adults. Younger adults use social networking sites at much higher rates than their older counterparts with nearly three fourths accessing them compared to 50% or less in older adults. In addition, the average age of a video game player was 37 with a 12-year history of game playing.

Finally, 29% of those who play video games are older than 50 and the numbers are steadily increasing (Entertainment Software Association, 2011; Gerling, Schild & Mausch, 2010).

Despite lagging behind younger adults in technology use in most categories, older adults do utilize technology more frequently than their younger counterparts in at least one area. According to the Center for Technology and Aging, 11% of adults over the age of 50 use mobile devices to track health metrics such as blood glucose, physical activity levels or blood pressure (2011). Other researchers also found that older adults' health-related use of technology exceeds younger adults (Olsen, O'Brien, Rogers & Charness, 2011). Finally, use of online e-health tools by older adults peaks before decreasing as age reaches the oldest old (McInnes, Gifford, Kazis & Wagner, 2010; McMillan & Macias, 2008).

Internet and Information

The Internet has been accessible and used by large portions of the population for many years. In addition, the ways in which the Internet has been accessed have changed rapidly as advances in connectivity have evolved from early dial-up connections to the high-speed and wireless connections of today. By the 1990's public health and health promotion professionals began to recognize that the Internet programs could potentially impact large portions of the population and increase preventive and health promoting behaviors (Cassell, Jackson & Cheuvront, 1998). In addition to information on prescription medications, diet and diseases such as cancer and arthritis, exercise is one of the most popular topics of interest online (McMillian & Macias, 2008).

The use of online resources to support healthy behaviors is much more developed than other forms of e-health tools. Even though electronic games, social networks and self-monitoring tools have existed for many years, their use to support health-related activities is still relatively recent. The Internet has been rapidly adopted as a primary channel for seeking health related information for large segments of the population (Kreps & Neuhauser, 2010). Regardless of its reach, gaps still exist in its utilization, often termed the “digital divide” and are usually related to lower education, lower socioeconomic status or increased age (Kreps & Neuhauser, 2010). Despite its limitations, the Internet can be a successful channel for delivering effective behavioral interventions that rival and sometimes exceed the effectiveness of standard lifestyle interventions for smoking cessation, self-efficacy and exercise and may even be the preferred method for receiving exercise information in certain groups (Marshall, Hunt & Jenkins, 2008). Furthermore, self-efficacy for the use of online resources can influence how frequently older adults use it (Chu & Mastel-Smith, 2010).

Age-related Differences in Online Resource Utilization

While there is inconsistent data about the degree to which individuals use the Internet for health-related activities (Kreps & Neuhauser, 2010; McInnes, Gifford, Kazis & Wagner, 2010), the Internet is often used as a primary conduit for health information among many different groups (Atkinson, Saperstein & Pleis, 2009; Brouwer et al., 2010; Cohall et al., 2011; Center for Technology and Aging, 2011; Koch-Weser, Bradshaw, Gualtieri & Gallagher, 2010). Younger adults, while significant users of the Internet in general, don't seek online health-related support as often as their older counterparts, though this trend isn’t linear since very old adults use the Internet less than all other adult groups (McInnes et al., 2010; McMillan & Macias, 2008). The possible explanation

for this difference may rest in the younger adult's perception of risk for illness. As a group, younger adults are typically healthier and are therefore not as inclined to seek online health information though this has not been empirically tested.

Older adults' attitudes and preferences for Internet related health support is shifting. Historically, lower prevalence rates of technology adoption have been associated with increased age, though incidence of technology adoption is increasing. Older adults have begun utilizing various forms of Internet support for health with some expressing a preference to use the Internet to communicate with their providers (Singh, Fox, Petersen, Shethia & Street, 2009). In a qualitative survey of older adults, older adults desire online access to several different types of health information, such as up to date treatment information, information so assist in choosing health providers, general health topics and information on diet and exercise (Xie, 2009). Among adults aged 55 and older, the methods most used for accessing online health information were search engines, commercial health sites and web portals like Yahoo (McMillian & Macias, 2008).

Online Resources and Exercise

Some longitudinal studies have demonstrated that certain Internet programs, when acting as a relational agent and providing information and feedback to users, can produce desired behavior changes in older adults (Bickmore, Caruso, Clough-Gorr & Heeren, 2005a; Bickmore, Gruber & Picard, 2005b). In addition, online programs can provide feedback and act as a virtual coach to improve physical activity (Watson, Bickmore, Cange, Kulshreshtha, & Kvedar, 2012) or weight loss (Hunter et al., 2008; Svensson & Lagerros, 2010) by providing supportive feedback on progress and a comparison to historical performance.

Social Cognitive Concepts and Online Resources

In addition to being a health information tool, the Internet can provide an avenue for participation in structured programs that can influence self-efficacy and behavior (Bandura, 2004). Theory based online interventions would be most successful on social cognitive concepts. For example, a longitudinal study examining the relationship between an intervention and changes in physical activity and eating habits found that online interventions can significantly improve steps per day of activity, and healthy food consumption (Anderson-Bill et al., 2011b). The web-based online intervention consisted of tracking physical activity, eating habits and receiving goals and general feedback over a 52-week period. These results supported earlier findings that online interactive programs are effective at improving self-efficacy (Kreps & Neuhauser, 2010).

Self-Monitoring and Exercise

Self-monitoring tools can support self-regulatory mechanisms such as feedback and goal setting. Using instruments that track data, contextual activities or feedback on data points provides the user with information regarding health behaviors. Significant effects of pedometers or other self-monitoring devices on various health behaviors such as disease self-management and exercise have been found (Heesch, Masse, Dunn, Frankowski & Mullen, 2003; Hollis et al., 2008). Even though little evidence exists about how different age groups use these devices, increasing numbers of adults are adopting self-monitoring health tools, especially with the introduction of mobile technology. According to the Center for Technology and Aging (2011), 11% of adults over the age of 50 use mobile devices to track health metrics such as blood glucose, physical activity levels or blood pressure.

Though not empirically tested, self-monitoring theoretically should enhance feelings of control, thereby boosting self-efficacy and influencing behavior (Bandura, 1997). The act of monitoring may influence behavior by raising awareness of the behavior that person is attempting to monitor. Self-monitoring tools provide feedback and can improve motivation, self-awareness and user satisfaction as well as increase the likelihood for sustained engagement with a weight loss program (Sevensson & Lagerros, 2010) or exercise program (Heesch, Masse, Dunn, Frankowski & Mullen, 2003).

In a randomized controlled trial comparing various methods for weight loss in obese adults, self-monitoring through food tracking, when included as part of a comprehensive intervention program, added significantly to a model of factors predicting short-term weight loss (Hollis et al., 2008). Further analysis in this study revealed that the online food tracking component, in conjunction with exercise, predicted greater weight loss in African Americans when compared to those who didn't track their food intake.

In a qualitative study of health professional and layperson's perceptions of self-monitoring tools, identified benefits of self-monitoring included: behavior change support, making behavioral patterns more evident, health monitoring data, challenging or validating beliefs, recording events, and supporting social interaction (Beudin, Intille & Morris, 2006). In addition, potential limitations included: tracking certain behaviors may not apply to the individual, won't provide new or valuable information, threatens self-image, leads to social conflict, forces too much structure, and can be too complicated, error prone or disruptive. Fogg and Eckles' (2007) work supports the identified benefits

of tracking using mobile devices that can persuade behavior change through social influences, providing feedback and contextual messaging.

Social Networking in Health & Exercise

All age groups are rapidly adopting social networking, though evidence points to differences in how quickly this is occurring. Facebook has grown to over 1 billion users within just a few years. Individuals are now able to connect with each other, share experiences, offer encouragement and provide guidance and feedback using these new tools. They are becoming so popular in fact, that many health-related websites now have some social networking aspect woven into them.

Social networking can provide support to those with chronic disease and 55% of Americans can get information about a therapy or condition online (Deloitte Center for Health Solutions, 2010). In addition, websites such as *Patients Like Me* provide a milieu whereby individuals can connect with others who share similar experiences, including ways in which they were able to overcome difficult circumstances and improve their own health (Deloitte Center for Health Solutions, 2010; Hwang et al., 2010). Even though social media use as a tool for health interventions shows promise, there are a few limitations. For example, the veracity of health information disseminated via social networks is sometimes questionable and using social networks as a vehicle for health interventions may exclude those socially disadvantaged, a group most often in need of health information (Chou, Hunt, Beckjord, Moser & Hesse, 2009).

Many factors influence how social networks can sway behaviors for various groups of individuals. Social networks increase interpersonal communications, thereby facilitating the transference of ideas, supportive statements, barrier identification and thought sharing among others (Bandura, 2004). Social networks can also be used to

facilitate awareness of health related topics. Indeed, social networks can increase the power and reach of health communications campaigns thereby increasing their effectiveness at changing behaviors (Chou et al., 2009; Kreps & Neuhauser, 2010).

While there is still some debate over whether open social networks such as Facebook, rather than health specific ones will be used by individuals for health-related functions, evidence is mounting that many prefer to use some form of social network in pursuit of better health (Fukuoka et al., 2011; Greene, Choudhry, Kilabuk & Shrank, 2011). For instance, the ability to form social networks in which to share barriers, experiences and feelings was indicated as an important characteristic of a mobile diabetes community (Fukuoka et al., 2011). These findings supported efficacy-building assertions by Bandura (1997), which indicated that social modeling and verbal persuasory interactions positively influence health behaviors.

Age-related Differences in Social Network Use

Significant age-related differences exist in the adoption and use of social networking technology. As would be expected, Millennials use social networking technology more frequently than older generations. For example, 75% of Millennials have created a social networking profile compared to 50% of Generation X, 30% of Baby Boomers and just 6% of members of the Silent Generation (Pew Research Center, 2010).

Even though they comprise the largest group of social networking users, social network technology adoption is not limited to younger generations. In fact, while the use of social networking by 50 to 64 year olds was only 7% in 2005, by 2010 that percentage had increased to 42% (Center for Technology and Aging, 2011). In addition, just 2% of the adults aged 65 and older used social networking in 2005 and by 2010

that number had increased to 6%. Utilization of social media can support older adults in the following ways: managing chronic conditions, promoting primary preventive measures and eliciting peer support while decreasing social isolation (Center for Technology and Aging, 2011; Gracia & Herrero, 2009; Patrick, Griswold, Raab & Intille, 2008).

Very few studies have been conducted testing the differences in the adoption of social networks by different age groups. However, limited evidence exists indicating that age significantly influences the adoption of social networks to support health (Chou et al., 2009). Cross sectional survey results revealed that age was significantly associated with Internet and social networking use. Further analysis using age stratified logistic regressions supported the significance of age as an influencer of social network use with increasing age being negatively related to social networking use for health.

Social Cognitive Concepts and Social Networks

While there is emerging evidence to support social networks as an efficacy building tool, more work needs to be done to test these effects. Social networks can influence health behaviors by overcoming various barriers (Maitland, 2011). Personal or environmental constraints such as lack of experience, unfamiliar exercise environments, social or familial limitations, or lack of exercise role modeling can be countered through the application of a social network. For instance, modeling of exercise behavior through social network exposure to exercisers who physically appear like the individual or that highlights alternative exercise methods and environments and provides affirmative reinforcement can influence exercise behavior. These strategies are congruent with efficacy building through social modeling and verbal persuasion.

Social networks can change behaviors through socially mediated paths of influence. In addition, social networks must be efficacy building in order to be effective and that sustained success in behavior change can be realized (Bandura, 2004). Social networks provide guidance, support and incentives relevant to the individual, thereby exerting influence and promoting behavior change. Social networks aimed at health behavior change must be structured to motivate, promote self-management and address health habits in order to be effective.

Empirical testing of social networking influences on health behavior adoption is in its infancy. However, in a novel approach to testing social network interventions, researchers conducted an experimental study to test the effects of homophily on the adoption of a health behavior within an online social network (Centola, 2011). Homophily is the tendency of individuals to construct social networks that are similar in characteristics to themselves. The sample included 710 participants of an online fitness website. Two groups were formed with one consisting of clustered groups by age, body mass index and gender and another, that was not grouped by any demographic variable. Within each group a single person displayed their use of an online nutrition journal to their social network. The researchers then measured how quickly a health behavior, nutrition journaling, was adopted by this person's social network as evidenced by initiating the online health journal and sending a notification that they began the journal behavior to their group. Those in the homogenous group significantly adopted the journaling behavior nearly three times faster than as many individuals ($p < 0.01$) than the control group. Furthermore, obese individuals adopted the behavior in the homophilous group twice as quickly as those obese individuals in the heterogeneous

group. These findings were congruent with suggestions by Bandura that social modeling influences behavior (1997, 2004). In a meta-analysis of interventions to increase exercise behavior in chronically ill adults, Conn, Hafdahl, Brown and Brown (2008) also found that adoption of healthy behaviors could be facilitated through social networks. Hence, social network influences impacts exercise participation in many different types of studies.

Electronic Games

Human beings have engaged in game playing since the beginning of history with evidence of games found preserved in ancient burial sites thousands of years old (Baranowski, Buday, Thompson & Baranowski, 2008). Playing games satisfies emotional and psychological needs by promoting feelings of competence, achievement, and satisfaction, and in solitary games, autonomy (Ryan, Rigby, Przybylski, 2006). While the playing of games is not new, the ways in which games are played has evolved considerably.

New technologies offer significant opportunities to engage people in activities aimed at improving health that are both fun and motivating. The use of games as health interventions is being explored more frequently although significant gaps in knowledge still exist. Digital games are being played on an ever-increasing basis and that they can be effective at improving physical activity as well as confidence in activity participation. In addition, games are no longer restricted to home use and can be played by many newer mobile devices (Li & Counts, 2007).

Using electronic games is becoming increasingly popular. In fact, the number of people who play electronic games in the U.S. numbers in the millions (Entertainment Software Association, 2011). In 2010, gamers spent 25.1 billion dollars on electronic

games and hardware with 72% of American households playing electronic games of some type. Gamers are also diverse, with female gamers (42% overall) over the age of 18 (37%) outnumbering male gamers 17 or younger (13%). As of 2011, the age of the average game player was 37 with a 12-year history of game playing. Finally, older gamers over the age of 50 represented about 29% of the American gaming population and the numbers are climbing (Entertainment Software Association, 2011; Gerling, Schild & Mausch, 2010).

Electronic games are able to provide fully immersive environments in which players can complete tasks, solve problems, and assume different identities. Historically, electronic games played at a computer or using a console were considered a health risk since interacting required little physical exertion by the gamer (Kautiainen, Koivusilta, Lintonen, Virtanen & Rimpela, 2005). However, gaming mechanics have changed from simple joystick controllers to ones augmented by accelerometers, infrared cameras or other motion sensing technology. Players can now control games using body movements, with or without the aid of handheld controllers. With the advent of motion based game controls, some forms of gaming have transitioned from a sedentary health risk to a tool to that can improve health by increasing physical activity. Electronic games are capable of reaching large, diverse audiences and can be experienced for extended periods of time while maintaining the attention of the player. Thus, making electronic games ideally suited as vehicles for behavior change (Baranowski et al., 2008).

Age-related Differences in Video Game Use

Experiential Timing

Electronic games have been a source of recreation for children and young adults for many years and are often used to socialize and share experiences with others in their age group. As games became commercially available in the late '70s and early '80s, individuals were able to engage in electronic game play at home as well as social venues like video arcades. Meeting at the arcade was often a social event in which young game players were able to interact with each other and play. Many individuals who were older at that time did not participate in gaming the way children did, therefore, their experience possibly shaped their idea that certain electronic games were for children.

Although not empirically tested, several investigators have suggested that timing of exposure to technology may influence the use of electronic games (Boschman, 2010; Ijsselsteijn, Nap, de Kort & Poels, 2007; Pearce, 2008). Age-related factors such as prior exposure to technology, cost perception and desire for instructions can influence how different games are adopted and enjoyed by different age groups. In a pilot study to explore patterns of adoption for exergames in novice users over 40 years of age, Boschman (2010), compared two exergames with exertive interfaces while assessing how instruction clarity impacts perception of the experience. In a qualitative interview, participants regarded certain types of gaming such as personal computer based games as appropriate for older gamers rather than console-based games, which were seen primarily for children (Boschman, 2010). Nearly all of the study participants stated that they played electronic games on a personal computer (PC) rather than a gaming console such as a Nintendo, a finding that was also observed by Pearce (2008).

Adults over 65 may possess characteristics that influenced their level of comfort using electronic games (Ijsselsteijn et al., 2007). For instance, they may have retired without using a computer at work and possibly learned computer games differently due to this lack of experience. Also, older adults tend to be fearful that they will damage the game and will consult user's manuals more frequently than younger players. Furthermore, Pearce conducted a mixed methods study of 300 Baby Boomers born between 1946 and 1964, and their use of computer games (2008). Almost half of the participants did not play their first game until they were 20 years old or older; with 16% not playing initially until after age 40. In addition, 76% received their first gaming system after age 20 and 16% after the age of 40. Further qualitative analysis revealed that they were fearful of breaking the games. Unfortunately the survey was delivered via a website, potentially biasing the sample towards those more comfortable using technology, though this was not addressed. In summary, timing of exposure to technology may influence its subsequent adoption.

Physical Changes

While experiential timing seems to influence how electronic games are adopted and in what format, other cohort characteristics may also play a role (Dunning, 2008b). Age-related changes affected the game interface for elderly players (Gerling et al., 2010). For instance, cognitive changes, sensory changes or presence of illness may limit the player's ability to process game information as quickly as younger players. Additionally, physical limitations may limit the range of motion or precision needed to successfully control the game.

Electronic exercise games may be a useful tool to increase physical activity in older adults (Dunning 2008a; Gerling et al., 2010). However, physical declination

normally associated with the aging process can raise challenges for older game players who wish to use exertive interfaces to exercise (Gerling et al., 2010). Game players who are not successful due to physical limitations may not find the experience enjoyable, thereby decreasing the likelihood of continued interaction.

The physical limitations of older adults or age-related differences should be taken into account when designing and providing older adults with video games. For instance, games should be flexible enough to allow various styles of game play to accommodate the physical limitations such as difficulty standing or maintaining balance. As in some dance games with team-based play, social interaction and teamwork are facilitated and many older adults find these enjoyable (Boschman, 2010; Dunning, 2008b). Also older adults preferred games with simplicity, adjustable displays, immediate performance feedback and fewer required steps (Gerling et al., 2010). Including these design features may improve older adult's enjoyment of exercise games.

Electronic games can be enjoyable for all age groups. In a cross-sectional study (Graves, Ridgers, Williams, Stratton, Atkinson & Cable, 2010), 14 adolescents aged 11 to 17 years old were compared to 15 young adults aged 21to 38 and 13 older adults aged 45 to 70. How much a person enjoyed an activity was the primary determinant of the likelihood of continued participation. Not only were the games enjoyable, but they also generated significant increases in oxygen consumption. While older adults preferred exergame interfaces using the balance board, all groups preferred exergames to traditional exercise.

Exergames, Health and Exercise

While some controversy exists regarding whether exercise games as a group can promote health, the evidence is clear that certain exertive interface video games

are beneficial and effective at generating energy expenditures needed to qualify as moderate exercise. In some studies, exergames did not produce energy expenditures needed to count as moderate physical activity, which is found to have health promotion benefits (Graves, Stratton, Ridgers & Cable, 2007; Graves, Ridgers, Stratton, 2008; Lanningham-Foster, Foster, McCrady, Jensen, Mitre & Levine, 2009). Miyachi, Yamamoto, Ohkawara & Tanaka (2010) countered that the measurement of energy expenditures was flawed in these studies. Often arm and leg movements were discounted thereby underestimating the amount of energy expended in exergames. Instead of measuring energy expenditure wearing a facemask as others have done, Miyachi and associates (2010) used a metabolic chamber that produced a far more accurate reading, than facemask measurements. They found that exergames do generate energy expenditures needed to reach moderate levels of physical activity.

In addition to generating energy expenditures needed to promote health, exercise games can also improve athletic performance as well as other health measures in adults. Warburton and colleagues (2007) found that interactive video game exercise significantly improved maximal oxygen uptake, leg power, and vertical jump height and reduced resting systolic pressure, when compared to control group performing standard exercise interventions. Interestingly, they found that adherence to exercise training was significantly higher in their intervention group and mediated the relationship between training and health outcomes. Therefore, participants using video games exercised more frequently, likely accounting for the improvement in health outcomes rather than the intervention itself. Similar significant findings were reported by others who found that electronic games were effective at increasing physical activity,

energy expenditure, oxygen consumption, and weight loss (Inzitari, Greenlee, Hess, Perera & Studenski, 2009), cardiorespiratory benefits (Siegel, Haddock, Dubois & Wilkin, 2009) and balance and leg strength in older adults (Nitz, Kuys, Isles & Fu, 2010).

An expert panel at the proceedings for the American Heart Association described several benefits of exergame participation, such as: improved confidence, social relationships and that participating in active gaming could have a “gateway effect” for other exercise experiences (Leiberman, Chamberlin, Medina & Franklin, 2011). For example, otherwise sedentary individuals would begin an exercise routine using the exergame then progress to other forms of exercise. Participants extended their exercise routines to include other traditional forms of exercise and also suggested that exergames make exercise more appealing across different age groups. This is of particular interest from a health behavior standpoint since it points to the relationship between exergames and increased exercise behaviors. The panel cited study results from the American Heart Association, which included 58% who stated they began other fitness pursuits such as tennis or walking after beginning an exergame-based fitness program. In addition, 82% of those surveyed stated they played more with family and friends, thus increasing social connectivity**.** Women were more likely than men to use exergames, to try new activities, stay active or challenge their physical limits. It is likely that through these self-efficacy improvements, participants were confident to engage in more traditional activities, which is consistent with Bandura (1997) that highly efficacious individuals are more likely engage in increasingly challenging tasks and remain resilient when embarking on a new activity. In addition to behavioral benefits, the authors noted several physiological impacts such as: improved energy expenditure,

vertical jump height, heart rate and blood pressure. Another physiological benefit was distraction from discomfort. Participants tended to participate regardless of painful perceptions, especially if social or collaborative aspects were included (Lieberman et al., 2011). Distraction from discomfort may counteract pain as a barrier to exercise in older adults.

Social Cognitive Concepts and Exertive Gaming

Exercise games are used by all age groups and are capable of producing numerous physical benefits and can produce health behavior changes. In a meta-analysis of games as behavior change tools, researchers found two mechanisms by which behavior can be changed by games that are consistent with Social Cognitive Theory (Bandura, 1997, 2004), 1) using behavior change techniques such using goal setting as a tool to play the game, or 2) using a story during the game to teach specific behaviors (Baranowski et al., 2008). Authors provided the example of learning self-regulatory goal setting in a story based game aimed at increasing fruit consumption among children as evidence how a theory-based change concept can be incorporated into a game so that as goals are set and achieved, healthy behaviors are learned and improved. Other game components found to be important to change behavior include: game immersion, interactivity and fantasy. However, games as health behavior change vehicles are in their infancy and require further study on their effectiveness at motivating different types of players.

Exergames and Barriers to Exercise

In addition to providing exercise and changing behaviors, exergames can help overcome barriers to exercise. Inzitari, Greenlee, Hess, Perera & Studenski (2009) conducted a qualitative study of post menopausal women aged 45-75 years old and

assessed their attitudes towards electronic dance game as tool for exercise. Women tended to adhere to dance based exercise programs and had fewer injuries when compared to traditional exercise. The investigators speculated that electronic dance games might promote exercise adherence through its system of rewards and feedback, which is consistent with self-regulatory motivators (Bandura, 1997). Focus groups identified barriers such as time commitment and weather. In addition, advantages of electronic dance games were: fun, increased social interaction, physical and mental benefits while reducing perceived barriers to exercise through convenience, not dependent on weather, easy to do in group or alone. Furthermore potential disadvantages were: difficulty in learning, long term adherence, technical aspects, cost, may not like music or dance style in game.

Exergames and Self-efficacy

In addition to influencing behavior, promoting social interaction, improving various physiological measures and increasing enjoyment, video games are also efficacy building. In one example, Bandura (2004) describes how in children video games build self-efficacy for self-care behaviors in chronic diseases such as asthma (Lieberman, 1997) and diabetes (Brown et al., 1997). The children engaged in various tasks which facilitated learning of diabetes management techniques such as insulin dosing and nutrition management. Follow up at 6 months demonstrated a significantly higher rate of diabetes control than those children who played non-health related games. In addition, self-efficacy for diabetes care was significantly higher as well as an increased ability to discuss various self-care techniques. The findings of others support a positive relationship between video game use and self-efficacy (Lieberman, Chamberlin, Medina & Franklin, 2011).

Thomas, Cahill and Santilli (1997) conducted an Intervention study with inner city adolescents and young adults (*n* = 324) using a computer based electronic game to increase self-efficacy for negotiating safe sex. Ages of participants ranged from 12 to 22 and were racially diverse. The game was designed to repeat various negotiating behaviors and reinforce simulated avatars completing the task. Intervention was specifically designed to boost self-efficacy through mastery experiences by repeating negotiating tasks in different computerized scenarios, and by social modeling through viewing ones digital self and others in similar situations successfully negotiation condom or dental dam use prior to an implied sexual encounter. Pre and post intervention knowledge regarding safe sex practices revealed a significant increase in knowledge within seven safe sex knowledge categories and safe sex negotiation. Participants with the lowest initial self-efficacy scores demonstrated the largest increase when compared to those who were already highly efficacious. Video games may boost self-efficacy and more work needs to be done in order to test whether exertive video games promote exercise self-efficacy.

Summary

Age-related differences exist in the utilization and perception of electronic resources. Older adults view electronic resources differently than their younger counterparts in that they tend to be more fearful in the use and are slower to adopt new technologies. Also, younger generations feel that technology is a defining characteristic of their group, a feeling that is not shared by older adults. Despite age-related differences, electronic resources can provide a mechanism to improve physical functioning, social interaction and confidence in behavior changes among all groups

while reducing perceived barriers and theoretically improving self-efficacy.

E-Health supports show promise in improving health through exercise but work must be done to understand which supports are effective at changing exercise behaviors. E-Health supports can fill a basic human need for social interaction, promote autonomy and might even build self-efficacy, but little is known about how their impact on this important concept. Furthermore, while age-associated characteristics might affect patterns of adoption for e-Health support use, little has been done to empirically test this.

As obesity rates climb and lifestyle-related disease proliferate, it is becoming imperative to find ways to engage individuals in their own health through personal action and controlling those risk factors on which they can have an impact. Many individuals can drastically improve their health risks and quality of life by engaging in behaviors like routine exercise. Unfortunately, many do not exercise as often as needed to prevent illness and promote health. Ways must be found to sustain individual engagement in health promoting behaviors so that the healthy period of life on the health/illness continuum is expanded, while illness and disease is compressed.

Significant technological advances in electronic health supports have flooded the population with tools promising to aid users in being healthy. Unfortunately, little work has been done to understand exactly how different ages utilize these tools and whether they are effective at influencing known components of health behavior. This research will add to current knowledge about self-efficacy and exercise among different age cohorts as well as support current understanding of how electronic health support tools are used by these groups.

CHAPTER 3
RESEARCH DESIGN AND METHODOLOGY

Design

This cross sectional study explored the use of e-health resources and their effects on self-efficacy and known factors that influence exercise behavior. A systematic random sample was obtained from participants that are stratified by different age-related cohorts. A survey was mailed to them to assess outcomes.

Sample

A stratified random sample was selected from potential participants in a nationwide wellness program, *The Prevention Plan.* This plan was an employer or health plan sponsored program that included employees and retirees of major corporations and state agencies. The *Prevention Plan* was a voluntary wellness program delivered online, telephonically or through paper-based learning modules based on preferences of participants. Stratification based on age cohort increased the probability that the study groups represented those in the Prevention Plan. Hence, comparisons of the cohorts in e-Health resource utilization, efficacy beliefs and social cognitive variables could be generalized to the population of persons in wellness programs.

There were a total of 96,287 potential participants in the wellness program. Of that number, 58.8% were female (n = 56,599) and 56.4% (n = 54,261) were employed either part time or full time. The overwhelming majority of participants were Caucasian (53.5%), followed by African-American (4.7%), Asian (2.5%) and Hispanic (3.4%), with the remaining individuals declining to state their race. Prevention plan member ages ranged from 3 years old to 110 with a mean age of 47 years, though only adults were

included in this study. Age distributions within each age category were as follows: Millennial (8.1%), Generation X (39.1%), Baby Boomers (47.8%) and Silent Generation (5%). Inclusion criteria were men and women ages 18 or older. Wellness program participation or access to a computer, video game system, self-monitoring tool or mobile phone was not used to exclude participants from the study.

Participants were stratified into age categories based on their age at the time of the study. Potential participants were grouped into the following four categories by age: Millennial: born since 1983 and aged 29 or younger; Generation X: born between 1965 and 1982 aged 30 to 47 years old; Baby Boomers: born between 1946 and 1964 aged 48 to 66 years old; and finally, the Silent Generation: born earlier than 1946 and aged 67 or older.

Power Analysis

Power analysis was conducted a priori with alpha set at 0.05, and β at 0.20 for a power of 80. In similar studies to the proposed, where relationships between social cognitive variables and exercise were tested, effect sizes of 0.30 (Hortz & Petosa, 2008) and 0.41 (Conn, Hafdahl, Brown & Brown, 2008) were found. According to Portney and Watkins (2009), correlational relationships between 0.25-0.5 indicate a small relationship, while correlations 0.5 and higher indicate moderate or higher relationships. A conservative effect size of 0.20 was selected as the minimum effect to be detected within the study. Using G*Power version 3.1.2 for Mac (Heinrich Heine University), with alpha set at 0.05 and a power of 80, the sample size needed to achieve the required power in this study is 280. There was a total of 70 needed in each age group.

Recruitment

Based on prior survey responses with the study population, a 15% response rate was estimated and used to determine the initial number of surveys to be sent. Using the required number to achieve power in the study (n = 280), divided by the response rate (15%) a total of 1,868 surveys was mailed, with 467 mailed to each age group. Recruitment continued until completed data was received on 70 participants in each group.

Thirty days after the initial surveys were mailed, analysis of returned surveys revealed if further recruitment was necessary to reach statistical power for each group. If a group remained underrepresented, having less that 70, an analysis to determine the number of new surveys to be sent commenced utilizing the following formula: (*70 – number of surveys received)/(0.15*). Reassessment of responses occurred 30 days after the second mailing. If recruitment was ultimately unsuccessful to reach required numbers, options to move forward with the study included grouping the two oldest groups together as one group and grouping the two youngest groups together. According to the Pew survey (2010), older aged cohorts (Silent Generation and Baby Boomers) did not define themselves using technology, while younger age groups (Generation X and Millennials) named technology as their defining characteristic, thus indicating logical clusters within the four groups.

Measurement

Study participants were mailed a questionnaire (see Appendix A) along with a cover letter (see Appendix B) introducing the survey, instructions and a postage paid return envelope. The anonymous questionnaire was included the following assessments: basic demographic information, exercise participation, exercise self-

efficacy, outcomes expectations for exercise, perceived barriers to exercise, e-Health support use and self-efficacy for e-Health support use. Survey headers were color coded by age group (Silent Generation=Red, Baby Boomers=Blue, Generation X=Green, Millennials=Orange) so that if age and year of birth was not answered, the survey data could still be used in the correct category.

The survey was written using plain language and organized so that common concepts were addressed together (Dillman, Smyth & Christian, 2009). For example, questions related to physical activity participation and social cognitive factors related to physical activity were grouped while questions related to each e-health resource were grouped as well. Instructions for completing each section were included and ambiguously worded questions were avoided. Arial 12-point font was used to increase readability especially for the older cohorts. It was anticipated that the survey would take no longer than 15 minutes, thereby increasing the perception that the survey would not be onerous to complete. There were no incentives to complete this survey.

Content validity for all developed questions was verified using an expert physician scientist with experience using survey instrumentation for health promotion. A Cronbach's alpha exceeding .70 was considered an acceptable level of internal consistency (Nunnaly & Bernstein, 1994). Corrected item correlations between .3 and .7 were considered evidence of a good scale (Ferketich, 1991).

Characterization of participants

Participant age, gender, marital status, educational level, geographic location, employment status and estimated number of years using a computer, mobile phone, video games and social networks were assessed.

Use of e-Health Supports

The taxonomy of e-Health supports described in the literature review was used to develop questions addressing each type of resource. Each e-Health category was defined in the questionnaire immediately preceding the questions to which they related. These were: Internet use, self-monitoring, social networking and exertive games. Respondents were asked first how many minutes per week they engaged in the use of the particular resource and how many minutes each week they use each resource to support exercise behavior. If a respondent did not use a particular resource, the score was zero for use and frequency for that resource. There were 3 scores: 1) total weekly minutes using each type of e-Health resource, 2) the total number of weekly combined minutes using all e-Health resources, and 3) The combined number of weekly minutes using all e-Health tools to support exercise behavior also by health resource.

Self-efficacy for e-Health Support Use

No current instrument existed to measure self-efficacy for e-Health support use though guidance exists on their construction (Bandura, 1997; 2006). Self-efficacy scales follow a similar pattern in which the respondent rates their level of confidence for a particular behavior. Efficacy scales should be unipolar, beginning at 0 with higher self-efficacy ratings coinciding with higher numbers on the scale. Also, scales should range from 0-10 or 0-100 and allow the user to choose between at least 11 intervals. Scales with fewer intervals lose differentiation in efficacy beliefs and are therefore discouraged. Finally, efficacy scales should assess current beliefs about operative capabilities rather than prospective or future-based assessments.

Accordingly, four questions were developed regarding confidence in using each type of e-health support. Respondents were asked rate their current level of confidence

for using each type of e-health resource on a Likert scale from 0 “not at all confident” to 10 “Very Confident” with higher levels indicating higher self-efficacy for e-health support tool use. The ratings were summed and the total score used to indicate self-efficacy for e-health support use. The same process was used to construct four corresponding questions rating self-efficacy for each e-Health tool used to support exercise.

The internal consistency of the self-efficacy for e-Health tool use overall scale was very good (Cronbach alpha = .80) and inter-item correlations between the four e-Health sub-scale items ranged between (r = .43) and (r = .58), indicating a strong relationship between the items. Also, corrected item correlations, which is the correlation between a single item and the rest of the items ranged from (r = .58) to (r = .68), indicating a strong single item relationship with the remaining combined scale items. Finally, no item, if deleted, improved overall Cronbach alpha, thereby indicating that all sub items should be included for the e-Health self-efficacy overall scale.

The reliability of the self-efficacy for e-Health tool use for exercise scale was also very good (Cronbach alpha = .82) and inter-item correlations between the four e-Health for exercise sub-scale items ranged between (r = .40) and (r = .65), indicating a strong relationship between the items. Corrected item correlations ranged between (r = .57) and (r = .72), indicating a strong single item relationship to the remaining combined scale items. Lastly, no scale item if deleted from the analysis, improved the overall calculated alpha, thereby indicating that all the sub-items for the self-efficacy for exercise e-Health tool use should be included.

Self-Efficacy for Exercise

Self-efficacy for exercise was assessed using the Self-Efficacy for Exercise (SEE) (Resnick, 2004). This was a nine question survey that participants rank their

exercise confidence on a scale from 0 “not at all confident” to 10 “very confident”. Internal consistency for the scale was sufficient (Cronbach alpha = 0.70). Responses were summed and the higher the overall score, the greater the individual’s self-efficacy for exercise. Evidence of validity was obtained through confirmatory factor analysis and hypothesis testing. Factor loadings were greater than .50 at baseline and follow up testing. All factors extracted were related to perceived confidence in the ability to exercise despite perceived barriers. For instance, one factor was being confident to exercise when the weather is not pleasant or in the presence of pain. These factors are consistent with theoretical expectations that highly efficacious individuals are resilient and engage in exercise despite barriers. Construct validity was also supported through hypothesis testing by statistically significant differences in exercise behaviors for those who had higher SEE scores than those who did not, which was consistent with theoretical expectations. For the current study, internal consistency was very strong for self-efficacy for exercise (Cronbach alpha = .94).

Outcome Expectations for Exercise

Outcome expectations for exercise were assessed using a 9- item Outcome Expectations for Exercise tool (Resnick, 2004). Respondents rated expected mental and physical outcomes of participation in exercise from 1 “strongly disagree” to 5 “strongly agree”. Evidence for construct validity was based on hypothesis testing and confirmatory factor analysis and through structural equation modeling (Resnick et al., 2001). Construct validity was supported by statistically significant differences in exercise behaviors for those who had higher outcome expectancy scores than those who did not, which was consistent with theoretical expectations. Results of structural equation modeling for the nine items included significant path coefficients ranging from .69 to .87

with outcomes expectations for exercise as the outcome, and evidence of model fit (X^2 of 69, *df*=27, *p*< .05, NFI = .98, RMSEA = .07). The ratings were summed with higher scores indicating greater outcome expectations for exercise. Internal consistency for the scale was very good in prior research (Cronbach alpha = 0.90) and was (Cronbach alpha = .87) in the present study.

Barriers to Exercise

The Barriers for Exercise scale was used to assess perceived barriers to exercise (Sechrist, Walker & Pender, 1987). The respondents rated barriers from 4 “strongly agree” to 1 “strongly disagree”. The ratings were summed and scores range between 14 and 56. Test-retest reliability was .77. Construct validity was established using confirmatory factor analysis. Factor analysis yielded a nine-factor solution initially which an explained variance of 65.2%. The 14-item Barriers Scale has strong internal consistency with Cronbach alpha in prior studies of .87 and .88 in this study.

Exercise Participation

Exercise participation was assessed using International Physical Activity Questionnaire (IPAQ) that identifies the frequency and intensity of physical activity completed on a weekly basis. The IPAQ measures physical activity for a wide range of adults (15-69 years old) and has been tested in numerous countries (Craig et al., 2003). Instrument validity was tested through corroboration of accelerometer-based measures of physical activity with measured estimates. Test-retest reliability correlations between instrument items were very good, ranging from .32 to .88 when repeated a week apart.

Estimates of physical activity are provided in minutes over the past 7 days and include descriptions of the different categories of physical activity. The total number of minutes in each category were summed, representing the amount of physical activity for

each category a respondent engages in weekly. Physical activity was considered “High” when one of the following criteria is met: Vigorous-intensity activity on at least 3 days, or 7 or more days of any combination of walking, moderate-intensity or vigorous intensity activities. Physical activity was considered “Moderate” under the following conditions: 3 or more days of vigorous activity of at least 20 minutes per day, 5 or more days of moderate-intensity activity or walking of at least 30 minutes per day, or 5 or more days of any combination of walking, moderate-intensity or vigorous intensity activities. Physical activity that does not meet the criteria for either high or moderate activity was considered inactive and is categorized as “Low”.

Procedures

The Prevention Plan donated administrative support to provide the identification, stratification, postage, mailing and data entry of survey results. The vice president (VP) for health intelligence generated the eligible list. Since age-related characteristics were of interest in this study and to ensure adequate representation from each group, all program members were loaded into a SQL database and a random number generator used to assign a unique identifier to each potential participant. Potential participants were further grouped into the following four categories: Millennial, Generation X, Baby Boomers and Silent Generation. Once grouped by age, the health intelligence VP sorted each group by the randomly assigned member number in ascending order. The total number needed in each group was determined using the total sample size (n = 280) divided by the number of groups so that there were an even number in each group (n = 70). Once sorted numerically, the first participants in each age group were selected to receive the mailed questionnaire. All potential participants were stored on a table for future use if needed. An analysis was conducted four weeks after the initial

mailing to determine response rate. In the event that response is less than 70 in each group, the stored tables were used in the same manner so that additional participants could be identified and surveys mailed until the required number in each category was reached. Throughout the process, the researcher was blinded to the sampling procedure and identification of study participants.

The researcher provided the survey list to a secure mail house provider to mail merge the participant list with the surveys, stuff envelopes, apply postage and send surveys to participants. Surveys were returned using the self-addressed stamped envelope. The researcher opened each survey and entered survey data into a Microsoft Excel™ spreadsheet. A second administrative person conducted a data entry integrity verification to check for keying errors.

Response data may differ on the returned surveys for some questions. For instance, in questions where the respondent is asked to estimate time in years or minutes, responses may be alpha or numeric. In addition, data may include fractions or decimals denoting partial years or minutes. Numerical data that is spelled out were converted to corresponding numerical values prior to entering into the spreadsheet. Fraction or decimal responses were rounded to the nearest whole number prior to entering into the spreadsheet. Initial administrative support training included how to handle data of these types.

Data Analysis

All data analysis was conducted using Predictive Analytics Software (PASW) version 18.0.3 (International Business Machines [IBM]). Descriptive univariate statistics was used to describe the population. Prior to statistical testing, all data was examined to determine whether it met the assumptions for parametric tests. In the event that the

data did not meet parametric assumptions, non-parametric methods were used for each specific aim if applicable. Logarithmic transformations were attempted in the event the data were not normally distributed. Missing data were identified. If age-related questions were not answered, the color-coded headers were used to group the survey into the appropriate age category. Mean replacements were used for questions where less than 10% of the data is missing. Surveys where greater than 10% of the data is missing were rejected.

For specific aim 1, total weekly minutes of e-health support use was tested for normal distribution using Shapiro-Wilk. If minutes of e-health support use not normally distributed, the Kruskal-Wallis test was used instead of analysis of variance. Homogeneity of variance was tested using Levene's test of equality of error of variances. Cases must meet independence assumptions and the number in each age group should be approximately equal. If assumptions were met, analysis of variance was used to explore the differences between the independent variable of age categories (Categorical) and total weekly minutes of e-health support use (Ratio). In the event that a significant group difference was found Wilcoxon pairwise comparisons were used to conduct post-hoc testing.

For specific aim 2, total weekly minutes of e-health support use was tested for normal distribution using Shapiro-Wilk. In the event that the total weekly minutes were not normally distributed, the Spearman Rho rank-order correlation coefficient was used (Burns & Grove, 2005; Portney & Watkins, 2009). Homogeneity of variance was tested using Levene's test of equality of error of variances. Scatterplot diagrams were used to determine linearity of the relationships. Careful attention was paid to outliers since

Pearson's correlation is sensitive to them. Influential outliers were examined and excluded from further analysis. If assumptions are met, then Pearson's correlation was used to explore the relationship between the independent variable of self-efficacy for e-health support use (ratio) and total weekly minutes of e-health support use (ratio).

For specific aim 3, total weekly minutes of e-health support use for exercise was tested for normal distribution using Shapiro-Wilk. In the event that the total weekly minutes were not normally distributed, the Spearman Rho rank-order correlation coefficient was used (Burns & Grove, 2005; Portney & Watkins, 2009). Homogeneity of variance was tested using Levene's test of equality of error of variances. Scatterplot diagrams were used to determine linearity of the relationships. Careful attention was paid to outliers since Pearson's correlation is sensitive to them. Influential outliers were examined and excluded from further analysis. If assumptions were met, then Pearson's correlation were used to explore the relationship between the independent variable of total weekly minutes of e-health support use for exercise (ratio) and SEE, OEE and BE (ratio). A priori adjustment of alpha to .01 was used to correct for family wise error.

Human Subjects

Institutional Review Board approval was obtained prior to initiating any research activities. Data integrity and security was protected using double-layer password protection for all computers. Paper files were maintained in a locked file cabinet within a locked room. All information was kept in accordance with Health Insurance Portability Accountability Act (HIPAA) security requirements. Individually identifiable information was removed and destroyed once it was no longer needed unless otherwise required by University policy. File destruction for paper materials will be conducted through a licensed, bonded and insured medical information destruction service. In addition, all

computerized files, including flash drives and other portable storage media were password protected/encrypted and will be degaussed if replaced. The researcher maintained only the minimum necessary information to complete the study. Study data were maintained in accordance with University policies and procedures.

CHAPTER 4
RESULTS

This purpose of this study was to describe the various electronic health supports used by different age cohorts, compare efficacy beliefs regarding these tools and to explore the relationship between e-Health support use and social cognitive concepts. The results of the data analysis include sample description, survey response rates, testing of assumptions and results of testing research questions. Data were analyzed using Predictive Analytics Software (PASW) version 18.0.3.

Sample

A total of 1,868 surveys were mailed initially, with 467 sent to each cohort. Figure 4-1 describes the survey mailing process over the data collection period. After the first six weeks, the surveys returned were: Millennial (*n* = 45, 10%), Generation X (*n* = 57, 12%), Baby Boomer (*n* = 84, 18%), Silent Generation (*n* = 66, 14%). Using the actual response rates for the first mailing, the number of surveys for a new mailing was calculated for each cohort. For example, using the Millennial response rate and the number still needed to reach 70, the following calculation was used: *(70-45)/(.10) = 250* new surveys were mailed. The same process was applied to the remaining groups that did not reach the minimum number of surveys needed. The final number of surveys mailed was 2,174 with a response rate of 13% overall.

Overall, the Millennials had greater weekly minutes of technology use than other generations. Millennials engaged in the use of social media about three times more minutes each week than even Generation X and nearly 5 times more minutes than Silent Generation. Greater detail regarding e-Health technology use by age cohorts is in Table 4-2.

Millennials

The millennial group was primarily female (67.1%) single (58.9%) and Caucasian (80.8%). The mean age was 25 years. They were well-educated with 80.8% having some or more college. Most were employed either part time or full-time (93.2%), and 61.6% reported annual household incomes greater than $35,000. Also, a majority (84.9%) reported moderate or high physical activity. (See Table 4-1)

Compared to the older cohorts, Millennials had the least years experience using computers (*M* = 14.3), mobile phones (*M* = 9.5), the Internet (*M* = 12.2) or self-monitoring tools (*M* = 0.91). By contrast, Millennials had the most experience using social networks (*M* = 6.7) and were second only to Generation X in their years experience playing video games (*M* = 8.5) (Table 4-2). Millenials spent the most weekly minutes of any group using the Internet (*M* = 945.3), social networks (*M* = 395.7) and playing video games (*M* = 102.2). Weekly minutes of self-monitoring tool use among Millennials was the second lowest (*M* = 21) of all the groups. (See Table 4-2)

Millennials had the highest self-efficacy for general technology use in each category as well as in support of exercise but with two exceptions. They were second to Generation X in their confidence using video games to exercise (*M* = 5.5) and self-monitoring tools for exercise (*M* = 6.3). By comparison, there was far less distinction in social cognitive exercise variables between the groups. Millennials were moderately confident in their ability to exercise (*M* = 54.4), had low perceived exercise barriers (*M* = 24) and had high outcome expectations for exercise (*M* = 37.5). (See Table 4-3)

Generation X

The Generation X group was primarily female (64.7%), married (62.7%) and Caucasian (80%) with a mean age of 38 years. Generation X respondents were very

well-educated with 93.3% reporting completing some or more college. Most were employed full or part time (90.7%) and were high earners with 66.7% reporting household incomes above $50,000. Nearly 85% reported moderate or higher physical activity. (See Table 4-1)

Compared to other groups, Generation X had the greatest experience with video games (*M* = 11.9) and were second highest in years experience with the Internet (*M* = 13.6), self-monitoring tools (*M* = 1.6), mobile phones (*M* = 12.8) and social networks (*M* = 3.8). Overall, Generation X was also heavy users of technology, though not to the same extent as Millennials. Generation X had the second highest weekly minutes use of the Internet (*M* = 518.0), social networks (*M* = 130.3), video games (*M* = 54.1) and self-monitoring tools (*M* = 57.3). They were also second in their use of e-Health tools to support exercise, but first in their use of video games to exercise (*M* = 8.8). (See Table 4-2)

Generation X was confident in their ability to use e-Health tools in general as well as for exercise. They were second to Millennials in their high confidence for Internet use (*M* = 8.96) as well as moderate confidence using social networks (*M* = 7.25), video games (*M* = 6.32) and self-monitoring tools (*M* = 6.36). Interestingly, Generation X had the highest confidence using video games (*M* = 5.67) and self-monitoring tools (*M* = 6.39) to exercise than the other groups. The Generation X group was moderately confident in their ability to exercise (*M* = 50.81) and perceived barriers (*M* = 25.04) and had high outcome expectations for exercise (*M* = 37.54). (See Table 4-3)

Baby Boomers

The baby boomer group was primarily female (59.3%), married (70.9%) and Caucasian (88.4%) with a mean age of 58.5 years. Baby Boomer respondents were

very well educated with 90.7% reporting completing some or more college. Most were employed full or part time (65.1%) or were retired (31.4%) and were the highest earners of any group with 68.6% reporting household incomes above $50,000. Similar to Generation X, nearly 85% reported moderate or higher levels of physical activity. (see Table 4-1)

Compared to other cohorts, Baby Boomers had the highest number of years experience with computers (*M* = 21.1), mobile phones (*M* = 13.3) and the Internet (*M* = 14.2). By comparison, they were next to last in their experience with social networks (*M* = 1.6). Baby Boomers were not heavy users of e-Health tools with one exception, they were first in their weekly use of self-monitoring tools overall (*M* = 97.9) and to support exercise (*M* = 106.0). (See Table 4-2)

Baby Boomers were confident in their ability to use the Internet overall (*M* = 7.95) and in support of exercise (*M* = 7.77), but had low confidence in the use of all other e-Health tools. Baby Boomers were moderately confident in their ability to exercise (*M* = 54.94), had moderate perceived barriers (*M* = 23.17) and high outcome expectations for exercise (*M* = 37.67). (See Table 4-3)

Silent Generation

The Silent Generation group was primarily male (58.3%), married (65.3%) and Caucasian (90.3%) with a mean age of 70.6 years. Silent respondents were very well-educated with 93.1% reporting completing some or more college. Most were retired (58.3%) or employed full or part time (36.1%) and were high earners with 68.1% reporting household incomes above $50,000. The Silent Generation was the least active of any group with 68.1% reporting moderate or higher levels of physical activity. (See Table 4-1)

When compared to the other groups, the Silents had the greatest number of years experience using self-monitoring devices (*M* = 2.3), second in years using a computer (*M* = 20.8), but were last in their experience with social networks (*M* = 1.2) and video games (*M* = 2.6). The Silent group were not heavy users of e-Health tools and were last in every category of technology use except weekly social network use (*M* = 75.8), video games (*M* = 36.5) and game use for exercise (*M* = 4.4) where they were second to last. (See Table 4-2)

The Silent Generation was moderately confident in their ability to use the Internet both in general (*M* = 6.52), and in support of exercise (*M* = 6.10). However, they had the lowest confidence of all the groups in their ability to use all other e-Health tools. Finally, the Silent Generation group was moderately confident in their ability to exercise (*M* = 51.17), had the highest perceived barriers (*M* = 21.12) and moderate outcome expectations for exercise (*M* = 34.76), which was the lowest of the four groups. (see Table 4-3)

Preliminary Analyses

Thirteen cases had missing data and were excluded from the analysis. The cases with missing data represented a very small portion of the overall sample (4.3%) and in some cases had greater than 10% of the overall data missing from the results. Recreating data through mean replacements would have yielded very limited benefit. Therefore all cases were excluded. Sample sizes, means, ranges and standard deviations for the outcome variables can be found on Table 4-4.

To assess the assumption of a normal distribution required for parametric statistical tests proposed for this study, skewness coefficients and Shapiro-Wilk tests were analyzed. Skewness coefficients (SC) less than -1 or greater than +1 were

considered highly skewed (Bulmer, 1979). A significant Shapiro-Wilk test indicates a non-parametric distribution of data (Field, 2009).

The total weekly minutes using eHealth resources across all groups was highly positively skewed (SC = +2.71) and had a significant Shapiro-Wilk ($p < .0001$). In addition, the total weekly minutes of using eHealth tool use for exercise was highly skewed (+9.56) and demonstrated a significant Shapiro-Wilk ($p < 0001$). In addition, eHealth self-efficacy was moderately negatively skewed (-.43) with a significant Shapiro-Wilk ($p < 0001$). Exercise self-efficacy, perceived barriers and outcome expectations were also skewed and were not normally distributed. Since all outcomes for technology use were significantly different than a normal distribution and transformation of the data did not resolve this issue, non-parametric methods were used.

In situations where analysis of variance assumptions are violated, a comparable non-parametric test can be used. The Kruskal Wallace statistic tests for differences in the distribution between groups and is based on ranked data (Field, 2009). As with the analysis of variance test, Kruskal Wallace only determines if a significant difference exists between groups, however, it does not provide detail about which groups are different. Therefore, post hoc tests were done to determine differences between the groups. The Wilcoxon rank sum test can be used for pairwise comparisons to determine significance. These multiple comparisons increase the likelihood of a type I error. The Bonferroni correction was used as a conservative measure to control for family-wise error. For six comparisons, an alpha of .0008 (*alpha .05 / 6 comparisons*) was used to assess significance of statistical tests.

Differences in e-Health Support Use (Research Question 1)

The difference between the generational cohorts for weekly minutes of e-Health support was significant ($X^2(3) = 44.49$, $p < .0001$). Millennial's weekly minutes of overall e-Health tool use was significantly higher than Generation X, Baby Boomers and Silent Generation. Likewise, Generation X's weekly minutes of e-Health use was significantly higher than the Silent Generation. Baby Boomers were not significantly different in weekly minutes of overall e-Health use than Generation X and the Silent Generation. (See Table 4-4)

Similar significant age-related differences were found in the weekly use of e-Health tools to support exercise ($X^2(3) = 31.75$, $p < .0001$). Millennial's weekly minutes using e-Health tools to support exercise was significantly higher than Baby Boomers and Silent generation. Generation X's use was significantly higher than Baby Boomers and Silent Generation. Finally, Millennial's use of eHealth tools for exercise was not significantly different than Generation X and Baby Boomer's were not significantly different than Silent Generation. (See Table 4-4)

Relationship of e-Health Use to Self-efficacy (Research Question 2)

A significant moderately positive relationship was found between the number of weekly minutes using e-Health tools and self-efficacy for e-Health tool use ($r_s = .50$, $p = .01$).

Relationship of e-Health Use for Exercise and Social Cognitive Exercise Variables (Research Question 3)

Weekly minutes of e-Health tool use for exercise was positively related to self-efficacy for exercise ($r_s = .21$, $p = .0003$) and outcome expectations for exercise ($r_s = .28$, $p = <.0001$). By contrast, weekly minutes of e-Health tool use was not significantly

related to perceived exercise barriers (r_s = -.05). Correlations between individual weekly minutes of e-Health tools and perceived exercise barriers were not significant: Internet (r_s = -.024), social networking (r_s = .014), video games (r_s = .083) and self-monitoring (r_s = -.114).

Table 4-1. Age Cohort Demographics

	Millennials (*n*=73)		Generation X (*n*=75)		Baby Boomers (*n*=86)		Silent (*n*=72)		Total (*n*=306)	
	n	%	n	%	n	%	n	%	n	%
Gender										
Male	24	32.9	26	34.7	31	36.0	42	58.3	123	40.2
Female	49	67.1	48	64.0	51	59.3	26	36.1	174	56.9
No answer	0	0.0	1	1.3	4	4.7	4	5.6	9	2.9
Marital Status										
Single	43	58.9	17	22.7	10	11.6	9	12.5	79	25.8
Married	27	37.0	47	62.7	61	70.9	47	65.3	182	59.5
Partnered	2	2.7	5	6.7	3	3.5	1	1.4	11	3.6
Divorced	1	1.4	5	6.7	9	10.5	9	12.5	24	7.8
Widowed	0	0.0	1	1.3	3	3.5	6	8.3	10	3.3
Ethnic Background										
African-American	6	8.2	6	8.0	4	4.7	3	4.2	19	6.2
Asian	1	1.4	3	4.0	2	2.3	2	2.8	8	2.6
Caucasian	59	80.8	60	80.0	76	88.4	65	90.3	260	85.0
Hispanic	4	5.5	2	2.7	1	1.2	0	0	7	2.3
Native-American	0	0.0	0	0.0	1	1.2	0	0	1	0.3
Pacific-Islander	3	4.1	3	4.0	1	1.2	1	1.4	8	2.6
Other	0	0.0	0	0.0	1	1.2	0	0	1	0.3
No answer	0	0.0	1	1.3	0	0.0	1	1.4	2	0.7
Education Level										
8th Grade or less	1	1.4	0	0.0	0	0.0	0	0	1	0.3
Some high school	2	2.7	1	1.3	0	0.0	1	1.4	4	1.3
High School Graduate / GED	11	15.1	3	4.0	8	9.3	4	5.6	26	8.5
Some College or 2 year degree	21	28.8	25	33.3	26	30.2	11	15.3	83	27.1
4 year college graduate	21	28.8	21	28.0	23	26.7	11	15.3	76	24.8
More than 4 year degree	17	23.3	24	32.0	29	33.7	45	62.5	115	37.6
No answer	0	0.0	1	1.3	0	0.0	0	0	1	0.3

Table 4-1. Continued

	Millennials (*n*=73)		Generation X (*n*=75)		Baby Boomers (*n*=86)		Silent (*n*=72)		Total (*n*=306)	
	n	%	n	%	n	%	n	%	n	%
Employment										
Full time	53	72.6	61	81.3	47	54.7	21	29.2	182	59.5
Part time	15	20.5	7	9.3	9	10.5	5	6.9	36	11.8
Unemployed	5	6.8	5	6.7	1	1.2	0	0	11	3.6
Retired	0	0.0	0	0.0	27	31.4	42	58.3	69	22.5
Volunteering	0	0.0	0	0.0	1	1.2	2	2.8	3	1.0
No Answer	0	0.0	2	2.7	1	1.2	2	2.8	5	1.6
Annual household Income										
< 10,000	4	5.5	2	2.7	0	0.0	0	0	6	2.0
10,001- 25,000	9	12.3	5	6.7	2	2.3	1	1.4	17	5.6
25,001 – 35,000	10	13.7	3	4.0	7	8.1	9	12.5	29	9.5
35,501 – 50,000	15	20.5	8	10.7	10	11.6	8	11.1	41	13.4
50,001 – 75,000	12	16.4	15	20.0	19	22.1	22	30.6	68	22.2
> 75,000	18	24.7	35	46.7	40	46.5	27	37.5	120	39.2
No Answer	5	6.8	7	9.3	8	9.3	5	6.9	25	8.2
Physical Activity										
Low	6	8.2	13	17.3	11	12.8	19	26.4	49	16.0
Moderate	25	34.2	31	41.3	40	46.5	30	41.7	126	41.2
High	37	50.7	29	38.7	33	38.4	19	26.4	118	38.6
No Answer	5	6.8	2	2.7	2	2.3	4	5.6	13	4.2

Table 4-2. e-Health tool Use by Cohort

	Millenials M (SD) Median [Range]	Generation X M (SD) Median [Range]	Baby Boomers M (SD) Median [Range]	Silent M (SD) Median [Range]
Years using				
Computer	14.3 (4.3) 15.0 [4-24]	19.3 (6.5) 20.0 [0-33]	21.1 (9.1) 20.0 [0-40]	20.8 (14.0) 20.0 [0-50]
Mobile Phone	9.5 (2.7) 10.0 [2-16]	12.8 (4.5) 14.0 [0-22]	13.3 (6.6) 15.0 [0-32]	10.2 (8.2) 10.0 [0-35]
Internet	12.2 (3.0) 12.0 [4-20]	13.6 (5.3) 15.0 [0-23]	14.2 (6.2) 15.0 [0-30]	13.2 (8.0) 15.0 [0-30]
Social Networks	6.7 (2.8) 7.0 [0-14]	3.8 (4.2) 3.0 [0-16]	1.6 (2.0) 0.0 [0-7]	1.2 (3.7) 0.0 [0-26]
Video Games	8.5 (8.5) 0.0 [0-28]	11.9 (13.5) 0.0 [0-35]	2.9 (7.1) 0.0 [0-30]	2.6 (6.3) 0.0 [0-25]
Self-Monitoring Devices	0.9 (1.8) 0.0 [0-10]	1.6 (2.7) 0.0 [0-10]	1.8 (4.5) 0.0 [0-25]	2.3 (5.8) 0.0 [0-32]
Weekly minutes of use				
Internet	945.3 (960.4) 600.0 [12-4000]	518.0 (615.1) 360.0 [0-2600]	510.5 (758.5) 200.0 [0-5040]	349.6 (488.4) 210.0 [0-2400]

Table 4-2. Continued

	Millenials M (SD) Median [Range]	Generation X M (SD) Median [Range]	Baby Boomers M (SD) Median [Range]	Silent M (SD) Median [Range]
Social networks	395.7 (529.8) 200.0 [0-2520]	130.3 (227.4) 45.0 [0-1500]	44.1 (99.3) 10.0 [0-700]	75.8 (324.1) 0.0 [0-2400]
Video games	102.2 (323.5) 0.0 [0-2500]	54.1 (125.3) 0.0 [0-840]	17.3 (63.0) 0.0 [0-420]	36.5 (114.5) 0.0 [0-600]
Self-monitoring tools	21.0 (46.8) 0.0 [0-30]	57.3 (193.0) 0.0 [0-1440]	97.9 (741.5) 0.0 [0-6720]	13.5 (44.1) 0.0 [0-270]
Weekly Minutes for exercise				
Internet	98.1 (343.1) 20.0 [0-2500]	17.9 (31.5) 0.0 [0-180]	15.1 (32.8) 0.0 [0-180]	7.3 (23.4) 0.0 [0-180]
Social networks	7.9 (19.5) 0.0 [0-120]	4.2 (12.4) 0.0 [0-70]	2.4 (12.9) 0.0 [0-60]	1.7 (14.3) 0.0 [0-120]
Video games	7.0 (22.7) 0.0 [0-120]	8.8 (28.7) 0.0 [0-210]	2.9 (17.8) 0.0 [0-150]	4.4 (27.3) 0.0 [0-200]
Self-monitoring tools	54.9 (28.4) 0.0 [0-2400]	88.1 (423.5) 0.0 [0-3600]	106.0 (743.5) 0.0 [0-6720]	51.3 (172.0) 0.0 [0-1080]

Figure 4-3. Social Cognitive Factors in e-Health and Exercise

	Millennials		Generation X		Baby Boomers		Silent	
	M	SD	M	SD	M	SD	M	SD
	Median [Range]		Median [Range]		Median [Range]		Median [Range]	
Self-efficacy								
Internet	9.3	1.2	9.0	1.4	8.0	2.4	6.5	3.0
	10.0 [5-10]		9.5 [3-10]		9.0 [0-10]		7.0 [0-10]	
Internet for exercise	8.9	1.7	8.3	2.2	7.8	2.7	6.1	3.5
	10.0 [2-10]		9.0 [1-10]		8.5 [0-10]		8.0 [0-10]	
Social network	9.1	1.4	7.3	3.2	4.6	3.6	3.7	3.3
	10.0 [5-10]		9.0 [0-10]		5.0 [0-10]		3.0 [0-10]	
Social network for exercise	6.9	2.9	5.9	3.4	3.9	3.6	2.9	3.0
	7.0 [0-10]		6.0 [0-10]		3.0 [0-10]		2.0 [0-10]	
Video game	7.1	3.3	6.3	3.3	3.9	3.3	3.5	3.4
	8.0 [0-10]		7.0 [0-10]		3.0 [0-10]		3.0 [0-10]	
Video game for exercise	5.5	3.4	5.7	3.3	3.7	3.3	2.5	3.0
	5.0 [0-10]		6.0 [0-10]		3.0 [0-10]		1.0 [0-10]	
Self-monitoring	6.6	2.9	6.4	3.1	4.8	3.3	4.8	3.4
	7.0 [0-10]		7.0 [0-10]		5.0 [0-10]		5.0 [0-10]	
Self-monitoring for exercise	6.3	2.9	6.4	3.2	4.8	3.6	4.3	3.6
	6.0 [0-10]		7.0 [0-10]		5.0 [0-10]		4.0 [0-10]	
e-Health tool use overall	32.0	6.2	28.9	8.3	21.2	9.9	18.2	10.2
	34.0 [13-40]		29.0 [5-40]		21.0 [2-40]		19.0 [0-40]	

Figure 4-3. Continued

	Millennials		Generation X		Baby Boomers		Silent	
	M	SD	M	SD	M	SD	M	SD
	Median [Range]		Median [Range]		Median [Range]		Median [Range]	
e-Health tool use for exercise	27.6	8.0	26.2	9.4	20.1	10.7	15.5	10.6
	28.0 [2-40]		27.5 [4-40]		20.0 [0-40]		14.0 [0-40]	
Exercise overall	54.4	20.7	50.8	24.6	54.9	22.6	51.2	28.2
	53.0 [0-90]		49.5 [0-90]		53.0 [0-90]		55.0 [0-90]	
Exercise Barriers	24.0	6.3	25.0	6.9	23.2	7.5	21.1	7.3
	24.5 [14-37]		27.0 [14-39]		22.0 [14-39]		20.0 [14-32]	
Outcome Expectations	34.5	5.8	37.5	5.6	37.7	5.8	34.8	7.9
	38.0 [23-45]		37.0 [22-45]		37.0 [21-45]		37.0 [13-45]	

Table 4-4. Age Differences in e-Health Use

	Millennials (N=73) *n* Mean(SD) Median [Range]	Generation X (N=75) *n* Mean(SD) Median [Range]	Baby Boomers (N=86) *n* Mean(SD) Median Range	Silent (N=72) *n* Mean(SD) Median Range	Chi-Square P value	Differences [a] Among Groups
Total weekly minutes using e-Health resources	n=71 1480.69(1409.80) 1020 [55-6795]	n=75 759.73(843.04) 515 [0-4440]	n=78 692(1142) 285 [0-7710]	n=69 476.52(748.14) 300 [0-5070]	$X^2(3)=44.49$ (p <.0001)	a > b, c, d b > c
Total weekly minutes using e-Health resources for exercise	n=71 171.52(447.39) 36 [0-2520]	n=74 120.53(434.63) 30 [0-3670]	n=78 128.06(765.92) 0 [0-6750]	n=69 58.43(183.11) 0 [0-1110]	$X^2(3)=31.75$ (p <.0001)	a > c, d b > c, d

[a] Significant differences between the groups using Wilcoxon pairwise comparison with Bonferroni adjustment ($p < .008$). a (Millennial), b (Generation X), c (Baby Boomers) and d (Silent Generation)

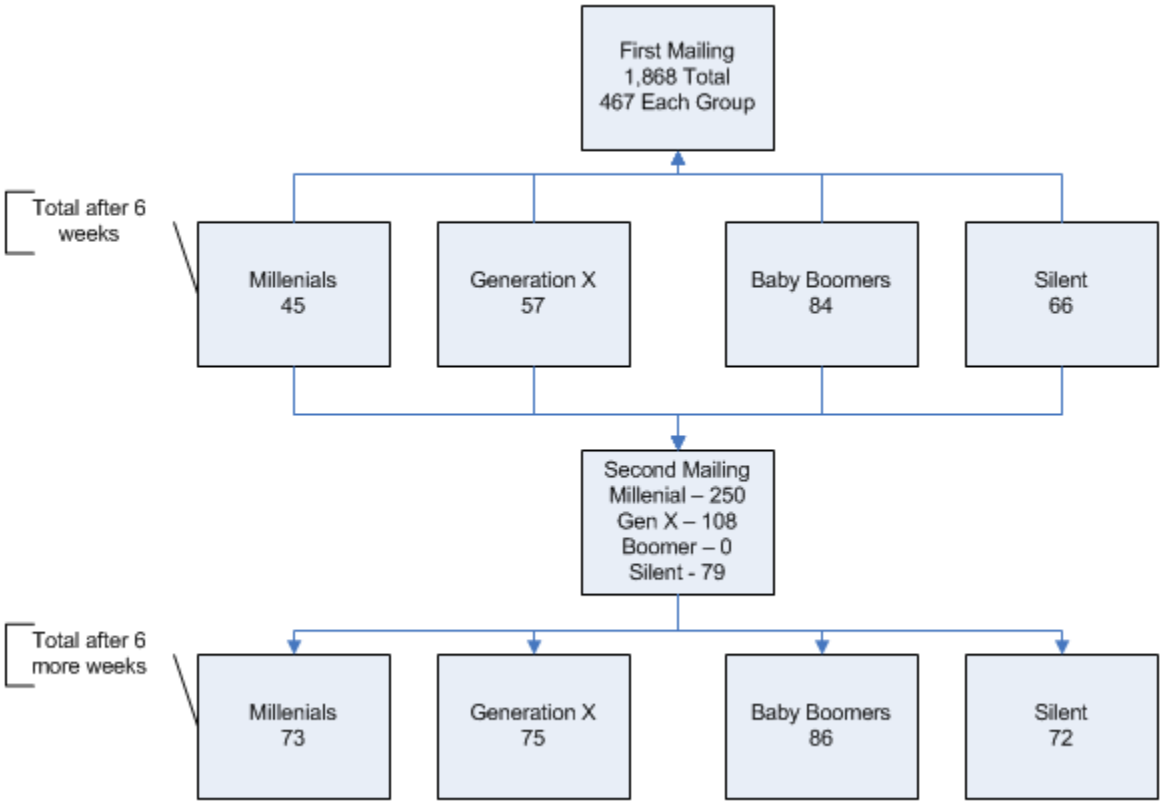

Figure 4-1. Survey flowchart

CHAPTER 5
DISCUSSION

Technological advances are changing the way in which health interventions are being delivered. From innovative and engaging web-based virtual coaches, to mobile wireless devices, smart phones and trackers, people are being exposed to new tools to improve their health. In fact, technology-mediated health behavior and self-monitoring is expected to grow to a multi-billion dollar industry by 2015 (Jackson, 2011). For example, projected revenue from just one component of e-Health, mobile health applications, is expected to quadruple to 400 million annually by 2016 (Empson, 2011). Another component of e-Health, disease specific wireless self-monitoring, is expected to grow as health care providers begin prescribing these tools to their patients (Topol, 2012).

Exercise is a well-known behavior that influences health and well-being and e-Health tools are being used more frequently to support it. In addition, evidence for the relationships between social cognitive concepts and exercise has been well documented. Some of the most downloaded mobile health applications today are related to fitness and frequently video games are being marketed for exercise. Social cognitive theory has been applied in multiple situations with varying effects, however a paucity of social cognitive research is focused on the relationship with e-Health tools. This research study was designed to explore age-related differences in e-Health tool use, identify whether their use was related to e-Health tool self-efficacy, and finally, to assess whether using these tools to support exercise was related to known social cognitive exercise concepts of self-efficacy, perceived barriers and outcome expectations.

A mailed survey was used to gather data from a random sample of participants in a national employer-sponsored wellness program. Not surprisingly, the younger cohorts were less responsive to a traditional mailed survey than the Baby Boomers and Silent Generation. Using only a mailed survey was an attempt to prevent biasing the sample towards those individuals comfortable with Internet use, which was a potential barrier to older respondents and was a variable of interest in this study.

The sample was primarily well-educated, married, Caucasian females, which was consistent with the workplace wellness population from which the subjects were drawn and other findings which demonstrated that this demographic is more likely to participate in worksite wellness programs (Person, Colby, Bulove & Eubanks, 2010). There were two notable exceptions to the sample demographic trends noted. First, Millennials were primarily single, which is consistent with the 15% marriage rate for this group in the US population (Madland & Teixeira, 2009). Second, unlike the proportion of males in the United States population over 65 years of age, the Silent Generation cohort was primarily male. According to the US Census, there are 1.4 times more women over the age of 65 than men, thus the ratio of men to women in this study was not consistent with the overall population, thereby limiting the generalizability of these findings to the U.S. population (U.S. Census, 2010).

Individual e-Health Tool Differences

While increasing age was associated with decreased use of e-Health tools in this study overall, distinctions were seen in the technology preferred by different cohorts.

Internet

The Internet was by far the most popular e-Health tool used by all groups in general as well as to support exercise and was negatively related to age. Previous

studies found a similar positive relationship between using the Internet for health-related activities and age (McInnes, Gifford, Kazis & Wagner, 2010; McMillan & Macias, 2008). By comparison, lower Internet use, both overall and to support exercise, was related to greater age in the present study. Possibly the definition of use of the Internet to support exercise rather than more broadly related to health information seeking in the present study may have masked the positive relationship seen by others. A broader definition of health activities would likely have included activities more relevant to older individuals such as disease management or illness prevention, a concern for these groups since disease burden increases with age.

Social Networks

When compared to the other groups, Millennial's use of social networks was much higher than the older age groups. In this sample, 97.3% of Millennials reported social network use that was 1.3 times higher than Generation X (76%), 1.8 times higher than Baby Boomers (54.8%) and 3.4 times higher than Silent Generation (28.6%). By comparison, Pew researchers found that Millennials (75%) used social networking 1.5 times more frequently than Generation X (50%), 2.5 times higher than Baby Boomers (30%) and 12.5 times higher than Silent Generation (6%) (2010). In the three years since the Pew study was conducted, social network use has continued to climb, and thereby may account for the higher rates of use seen in the present study. Regardless of the differences in the proportion of the generations using social networks, the negative relationship between age and social network use was evident and consistent with the declining relationship in general social network use seen in the Pew study.

Overall, social network use to support exercise was low (12.7%) across all cohorts. Compared to social network use in general, its use as a tool to support

exercise was limited. In addition, social network use for exercise was negatively related to age, which supported earlier studies where increasing age was associated with lower social network use for health (Chou et al., 2009). It is important to note that while this negative relationship between social network use and health was seen in previous studies, the health focus of the present study was exercise, thus the comparability of these findings is limited.

Video Games

In the present study, Generation X had the greatest number of years experience with video games, and a greater proportion of them used video games to support exercise than any other group. This finding was not surprising considering they were the first age cohort group to have access to video games at an early age. Timing of exposure to video games may influence their use (Boschman, 2010; Ijsselsteijn et al., 2007; Pearce, 2008). While using video games to support exercise would appear to be a likely intervention for Generation X, further study should be conducted to ascertain whether Millennials, who were exposed to video games even earlier than Generation X, use video games to exercise with increasing frequency over time. Finally, the upward trend in recreational and exercise video game use by Silent Generation seen in the present study should be explored further as it may hint to a growing acceptance of video game use by this age group.

Self-Monitoring

Self-monitoring was the most popular e-Health tool used to support exercise in all but the Millennial group. Baby Boomers were not heavy users of e-Health tools with one exception. They were first in their weekly use of self-monitoring tools overall and to support exercise. The rate of self-monitoring tool use by Baby Boomers and Silent

Generation in this study was 29.5%, which was considerably higher than the rate of self-monitoring tool use (11%) found by the Center for Technology and Aging for adults older than 50 (2011) and higher than the rate (27%) for all adults found by Fox (2010). The study sample, drawn from a group of worksite wellness participants, may have been more motivated to engage in health activities, possibly accounting for the difference in findings of the studies. Self-monitoring tools may be attractive to Baby Boomers and Silent Generation due to the relative simplicity of their design and use.

Pedometers have been used to track walking activity for many years and the user interface on these devices usually consists of few buttons and little extraneous information. These types of user interfaces are preferred by older adults and are important considerations when using an e-Health tool for this group (Gerling et al., 2010). While not assessed in this study, testing for differences in Smartphone application-based self-monitoring tools versus more traditional pedometers in older adults would guide understanding about future development of self-monitoring tools for Baby Boomers. Possibly, age-related increases in chronic disease and physical limitations make walking an attractive exercise option, which is the primary exercise tracked by pedometers. Finally, older adults tend to have more free time since they often do not work full time or are retired. Hence, they can devote more time to walking and would be more likely to be interested in using these tools.

Patterns of Use

Several patterns emerged in individual e-Health tool use that were of interest. The weekly minutes of e-Health tool use declined consistently with increased age: general Internet, Internet for exercise and social networking use for exercise. Both general and exercise self-monitoring tool use increased with age, peaking with

Generation X and Baby Boomers before declining in the Silent Generation. Finally, general social network use, general game use and games used for exercise declined with age until reaching the Silent Generation, where they began to increase.

This uptick in some e-Health tool use at the older end of the age spectrum suggests that older adults are in fact using these tools with increasing frequency that is consistent with earlier research with similar findings (Entertainment Software Association, 201; Fox, 2010; Gerling, Schild & Mausch, 2010). In the case of social network use by the Silent Generation, this increase may reflect the importance older adults place on maintaining social connections that have been observed by others (Barrett, 2011; Burnett, Mitzner, Charness & Rogers, 2011). Also, with advanced age, greater emphasis is placed on health, which may influence increased use of these tools.

Overall e-Health Differences Among Generations

Different types of e-Health tools may be used simultaneously, and significant differences among the cohorts were found for total weekly minutes of all e-Health tools. Post hoc comparisons among the cohorts revealed that Millennials utilized e-Health tools more frequently than their older counterparts. Unexpectedly, Generation X's general e-Health tool use was not significantly higher than Baby Boomers. In contrast, the Pew study (2010) revealed that Generation X was more similar to Millenials in using technology than their older counterparts. The exact reasons why these differences exist is still unclear, however reasonable inferences based on the characteristics of each cohort may point to several possibilities. For instance, the age or context in which technology was first introduced may influence beliefs about the usefulness or necessity of technology use in general. Introduction to technology at a younger age, while

formative processes are still active, may influence persistence of technology use in later life.

A similar significant difference was observed in e-Health tool use for exercise and subsequent comparisons were more consistent with expectations. Again, Millennials used e-Health tools to support exercise significantly more than Baby Boomers and the Silent Generation; nonetheless they were not significantly higher than Generation X that was suggested by the Pew study (2010). However, these findings conflict with Olsen, O'Brien, Roger & Charness's (2011) work that found that older adults used technology to support health more than younger adults. The difference may be related to the reason for e-Health tool use. In the present study, e-Health tool use was focused on exercise, which is a specific subset of health behaviors, rather than health in general. Study results might have been consistent with Olsen and associates if the target behavior was focused on disease management as disease burden increases with age.

Differences in Social Cognitive Factors Among Cohorts

Self-Efficacy for e-Health

Self-efficacy for e-Health tool use, both overall and for exercise, followed a consistent pattern that was negatively related to age. Younger cohorts were generally more confident in their ability to use e-Health tools in both contexts. This pattern was also consistent with the age-related declines in actual use of e-Health tools described in above sections. Specifically, the minutes spent using e-Health tools significantly decreased with greater age.

Baby Boomers surpassed other groups in their years experience using computers, mobile phones and the Internet. Even though they had the most years experience with these technologies, their confidence and frequency of use was lower

than Millenials and Generation X. While social cognitive theory would suggest that years experience would increase confidence thereby prompting use, the pervasiveness of technology use by younger groups, the age that it was first experienced and frequency of use may be more influential on e-Health efficacy beliefs (Bandura, 1997).

Exercise

Perceived exercise barriers were significantly lower for Millennials and Generation X than Baby Boomers and the Silent Generation. Perceived barriers were not significantly higher between Generation X and Millennials and were not significantly higher between Baby Boomers and the Silent Generation. Perceived exercise barriers can take different forms and are often dependent on age, cognitive ability, disease burden and the environment. Thus, this was not an unexpected finding because perceived exercise barriers increase with age and declining physical abilities (Deshpande et al., 2008; Ham, Sloane, Warshaw, Bernard & Flaherty, 2007).

By contrast, exercise self-efficacy and outcome expectations were not significantly different among the age groups. This was somewhat surprising because exercise self-efficacy would likely be higher in younger individuals who have not yet experienced age-related changes and health concerns typically affecting the exercise self-efficacy beliefs of older cohorts (Deshpande et al., 2008; Ham, Sloane, Warshaw, Bernard & Flaherty, 2007).

Relationships Between Social Cognitive Factors and e-Health

Weekly minutes using e-Health tools were significantly and positively related to the self-efficacy for e-Health tool use. This relationship is consistent with social cognitive theory that describes a positive relationship between self-efficacy and the desired behavior (Bandura, 1997). Greater weekly minutes of e-Health tool use overall

and specifically for exercise were associated with greater exercise self-efficacy and outcome expectations for exercise. As Bandura posited, self-efficacy is specific to a particular action or behavior (1997). This lends support to findings by others who suggest that using e-Health tools can build self-efficacy (Fukuoka et al., 2011; Greene, Choudhry, Kilabuk & Shrank, 2011).

Increased outcome expectations for exercise were significantly related to increased e-Health tool use for exercise. Therefore, those who used e-Health tools to support exercise had more positive expectations of the benefits of exercise overall. Even though no research has been done exploring the relationship between outcome expectations for exercise and e-Health tool use, these findings are theoretically consistent with relationships between outcome expectations and behavior (Bandura, 1997).

The small negative relationship between weekly minutes of e-Health tool use for exercise and perceived barriers was unexpectedly not significant. This was surprising since e-Health tools such as exercise video games (Inzitari et al., 2009) and social networks (Maitland, 2011) have been reported to lower perceived barriers to exercise. The expected relationship was not seen even when assessing the relationship of perceived barriers with video games use for exercise, and social network use for exercise. It may be that the technological nature of these tools is in some way a barrier themselves though this has not been tested.

Limitations

Using a mailed only survey design increased the cost of the study and may account for the low response rate. Since the survey was in English, non-response bias may be a factor, as potential participants who were more comfortable using another

language may not have responded. Age-related cohort differences in technology use identified in this study may account for the slow response by the younger cohorts. Since the younger cohorts define themselves by their use of technology, using an Internet survey methodology would be prudent and more likely to increase the response of these cohorts (Pew, 2010). Mixed method approaches that utilize both mailed and Internet surveys are reliable and should be considered if age-based comparisons are of interest, though they must be tested for equivalence prior to deployment (Dillman et al., 2009).

The survey response rate was low among all the cohorts and the sample may hence not be representative of the population. Also, the sample was fairly homogenous, composed primarily of Caucasian female English speakers, thereby limiting the generalizability of these findings to other demographic and ethnic/racial groups. In addition, the sample was highly educated with higher incomes that may have increased their use of technology (Noar & Harrington, 2012). Those less educated or below the poverty level may not have access or understand how to use some types of technology may not be inclined to respond to surveys about technology use, however there was not enough data in each cohort to determine this. Comparisons with the Pew Center survey (2010) are not possible because demographics of the responders and response rate were not reported.

The sample demographics were consistent with the workplace wellness population from which the subjects were drawn and other findings which demonstrated that this demographic is more likely to participate in worksite wellness programs (Person, Colby, Bulove & Eubanks, 2010). Thus, the sample was already likely to be engaged in wellness activities. For example, unlike their age cohorts in the general

population, the participants were overall moderately or highly physically active potentially biasing the results, though this could not be confirmed due to the anonymous nature of the survey and the researcher being blinded to the sampling. Being active already may have mitigated their perceived exercise barriers or meant they were already efficacious related to exercise. The age distribution of members of the wellness program were not consistent with the U.S. population since this program was delivered primarily as an employer-sponsored program.

This study was focused on the health behavior of exercise and did not address other health related functions e-Health tools could support. While these findings contribute to understanding e-Health tool use overall and to support exercise, other potential health behavior contexts were not explored. For example, e-Health tools can be used to monitor and manage chronic conditions such as diabetes while the present study only focused on exercise. While the findings support a relationship between efficacy beliefs and e-Health tools specific to exercise behavior, causality between e-Health tool use and improved exercise self-efficacy cannot be inferred in the present study.

Clinical Implications

Often health promotion programs have limitations in size, scope or funding, so targeting a health intervention using an e-Health tool preferred by a particular age group would be useful. As these tools are increasingly being used to support health behavior, it is important to consider age differences in e-Health tools to target them to a population with the greatest chance of being utilized. For example, Generation X and Millennials use social media and the Internet more frequently than other older cohorts in the present study. Thus, the younger cohorts may be more responsive to these

technologies than the older ones. Also, in this study, Generation X used video games more frequently and would be more likely respond more to these types of tools for exercise and health than older age groups. Even though older adults are using technology more frequently, providing these tools to an older patient may present a barrier if age-related differences such as self-confidence using technology or technology preferences are not considered. This information may be especially useful in targeting interventions such as Internet campaigns for older adults or delivering an exercise intervention via a video game to younger groups.

E-Health technology is being used increasingly as a tool for disease support and self-management. The overburdened healthcare system is bracing for the silver tsunami of Baby Boomer retirees who will begin to require health care services as they age. This confluence of technology and demand for health care provides opportunities and challenges to develop effective e-Health strategies for greater self-management and promote long-term independence. Care must be taken to ensure that e-Health tools used with older adults be considerate of their differences. Baby Boomers and the Silent Generation may perceive certain e-Health technologies such as video games as a barrier rather than a helpful tool. In addition, while social networks to promote health may appeal to younger groups, older adults may not find them useful. As a group, Baby Boomers will force the healthcare system to change as there will not be capacity to meet their needs using current resources. Conversely, Baby Boomers and Silent Generation will need to explore personal health-related technology use as it will continue to be deployed in clinical settings and extend into the home. In-home self-management of disease and health promotion will become critical to delivering

healthcare in the future so that inpatient, long term, skilled and assisted care will be minimized. Providers will continue to use e-Health tools more frequently to manage and monitor their patients remotely. In addition these tools will provide new levels of connectivity to the provider.

Designing e-Health tools for specific populations should include consideration for the users' age and e-Health tool preferences. Creating an e-Health tool for an older user should account for the age-related visual and cognitive changes so that the experience can be less overwhelming and more enjoyable. Keeping the user interface clean, without extraneous details and simple, concise instructions will aid usability for older adults. In addition, older adults' physical limitations such and mobility and balance may make some e-Health tools difficult or uncomfortable to use. Having ergonomically designed controllers or games in which the player is able to set the difficulty or controller characteristics to suit their physical limitations would be beneficial. While many e-Health tools such as mobile applications are free and are being provided as part of existing condition support programs at no additional cost to the user, other technologies may be expensive, thereby reducing their appeal to those with limited incomes.

Increasing self-efficacy for e-Health tool use may increase the likelihood the tool will be used. Social cognitive theory provides guidance on ways to improve self-efficacy that can be adapted to improve e-Health tool self-efficacy. Health care professionals should familiarize themselves with the various types of e-Health tools available, how they are used and which ones are effective. Providing a tool or prescribing one to be used without consideration for an individual's level of confidence would impact the efficacy of the e-Health tool in supporting the intended behavior. A user's level of

confidence should be assessed prior to using an e-Health tool as an intervention. If e-Health self-efficacy is low, then specific instructions, verbal encouragement or simpler initial tasks, which are easily mastered, will build confidence and familiarize persons with the tool and how it should be used. Therefore adequate training and social support are essential.

In the not too distant future, data from e-Health tools will be integrated into the medical record, and practitioners will need to understand the implications. It will become common to have patients who are using wireless devices, connected to mobile applications and managing conditions at home. Their data more than likely will be wirelessly connected to their provider, disease management nurse or health coach. Therefore these providers will be expected to support these new data streams and provide guidance to e-Health tool users in their practice.

E-Health tools should be designed so that they address the theoretical underpinnings of health behavior. E-Health tools should include components that will improve user self-efficacy through mastery experiences, vicarious learning, verbal persuasion and overcoming physical and emotional states. In addition, they should be constructed to reduce perceived barriers to their use and improve outcome expectations. They should include features such as task progression so that early mastery can support initiation of more challenging tasks and improve efficacy beliefs. For example, rather than an e-Health tool immediately focusing on a complete dietary change, it should start with smaller tasks such as simple food journaling before progressing to more difficult changes. E-Health tools should include self-regulatory mechanisms so that the user can see and track their progress towards a goal.

Research Implications

Using a mixed methods or Internet only survey approaches may increase response rates and mitigate non-response bias found in the age groups in the present study. If a technology-based survey is used, then other potential confounds such as lack of Internet access can lead to response bias. The digital divide, while shrinking, still impacts those whose characteristics may be of interest in e-Health research, such as the poor or uneducated. Further research sampling random zip codes or populations such as local community residents not engaged in wellness activities might yield results more representative of the U.S. population.

Despite the contribution to the evidence the findings of this research provides, further study of e-Health tools is needed. While significant age-related differences were found in use of e-Health tools, there is not yet compelling evidence that experiential timing has an impact on the use of these tools. For example, older adults had greater years experience with many of these tools, however self-efficacy and actual weekly use was much lower than younger groups. Future research is needed to explore the relationship between the age at which a person was first exposed to e-Health tools and current usage patterns.

Also, the expected relationship between e-Health tool use for exercise and perceived exercise barriers was not seen. Exercise barriers such as an unsafe environment or lack of time should logically be mediated by an exercise intervention that could be done in the safety of the home. The observed upward trend in video game use by the Silent Generation seen in this study may hint to a growing acceptance of video game use by this group. E-Health tools such as video games are often marketed to be

a safe and convenient alternative to traditional exercise, and research is needed whether these games reduce barriers to exercise.

There is limited data comparing the effectiveness of e-Health tools constructed using a theoretical framework to those currently in the marketplace. Without research-based evidence assessing the efficacy of e-Health tools, consumers are left to the advertisements of manufacturers to determine whether a tool is safe and effective to use. Randomized controlled trials are also needed to determine the effectiveness of e-Health tools. These will provide greater clarity about their efficacy and will begin to show that they do what they are advertised to do. Finally, very little work has been done about long-term engagement with e-Health tools. If these tools are used initially to support health, do users continue to engage with them over time? Also, if e-Health tools are effective, is this impact on behavior a long term benefit or do the effects lessen?

In addition e-Health tool use for exercise, additional research should be conducted to determine whether certain types of e-Health tools are more effective for some behaviors over others. For example, is using a video game to impact exercise behavior as effective if it's used to control diabetes? Are self-monitoring tools more effective for dietary management or medication adherence? Finally, this research has focused primarily on the independent use of e-Health tools; however, as these technologies evolve and incorporate aspects from different e-Health tools, does this generate an additive effect on the target health behavior?

Conclusion

E-Health tools show great promise such as broad reach, consistent interventions and reduced cost, however there are many unanswered questions. With such a rapid proliferation of available tools and the relatively short period since their application to

health, little is still known about the ways in which the public uses these tools, perceptions and beliefs about their use and whether or not they are effective. With over 40,000 health-related applications available, it is easy to see how poor design can infiltrate consumer products, which at minimum won't work and at their worst, can injure (Cohn, 2012). As Noar and Harrington (2012) point out, this rapid expansion has not allowed sufficient time for scientific inquiry to determine which approaches are safe and effective.

Demand for e-Health tools will continue to increase as the U.S. population ages and the need for cost effective alternatives to manage health and disease are needed. In home wireless disease management monitoring, exercise gaming, tracking and integrated Smartphone applications are being used to improve health at a lower cost than traditional methods of self-management. E-Health tools should be used to improve health though they should not be used indiscriminately. Some tools may be adopted and utilized with greater ease if appropriately applied. Furthermore, care must be taken to include behavioral science and clinical evidence in the development of these tools. If these tools are not constructed in a way that supports health behavior theories, then their effectiveness may be hindered.

Using a technology simply because it's in vogue or is "cool" is not reason enough to use it as a health intervention. As Bandura points out, repeated failures can erode self-efficacy (1997). If these tools don't work due to poor design or without consideration for the target population, the user may interpret their lack of progress as personal failure thereby impacting their self-confidence. As this research shows, social cognitive theoretical concepts continue to be evident, even when using emerging

technologies. Thus, e-Health tools that are intended to change or support health behavior should incorporate efficacy-building mechanisms to enhance effectiveness.

APPENDIX A
SURVEY

Remember your answers are anonymous and will not be shared with your employer or health insurer.

***Let's get started* - Basic Information (Please Print)**

Gender ***(circle)***: Male Female Age: _____ Birth Year (*yyyy*): _____

In which state do you live? ***(please print)*** _____

1. What is your marital status? ***(please check)***

   - O Single
   - O Married
   - O Partnered
   - O Divorced
   - O Widowed

2. What is your ethnic background?

   - O African-American
   - O Asian
   - O Caucasian
   - O Hispanic
   - O Native American
   - O Pacific Islander
   - O Other

3. What is the highest grade or level of school that you have completed?

   - O 8th grade or less
   - O Some high school, but did not graduate
   - O High school graduate or GED
   - O Some college or 2-year degree
   - O 4-year college graduate
   - O More than 4-year college degree

4. What is your employment status?

   - O Currently employed, full time
   - O Currently employed, part-time
   - O Unemployed
   - O Retired
   - O Volunteering

5. What is your annual household income?

   - O Less than $10,000
   - O $11,000 – 25,000
   - O $25,001 – 35,000
   - O $35,001 – 50,000
   - O $50,001 – 75,000
   - O More than $75,000

6. How many years have you been using a computer? ***(enter zero if you don't use a computer)***

   _____

7. How many years have you been using a mobile phone? ***(enter zero if you don't use a mobile phone)***

   _____

Page 1 of 10

Turn over to next page →

In this section you will be asked questions about different types of technology and how you use them.

Using the Internet/Going Online

8. Do you use the Internet? *Please include Internet use at home, at work or on a mobile device like a smart phone or tablet computer.*

☐ **YES**

☐ **NO** ⟹ ***If "No" skip to question 12***

9. How many years have you been using the Internet? ____ **years**

10. How many total minutes do you spend **each week** using the **Internet**? *Please include activities like web-browsing, viewing websites, shopping or searching for information.*

____ **minutes (enter "0" if none)**

11. How many total minutes do you spend **each week** using the **Internet** to learn about **exercise**? *Examples include activities like web-browsing, viewing fitness websites or searching for exercise information.*

____ **minutes (enter "0" if none)**

Now please rate your level of confidence, circle one number between 0 and 10. 0 means "'Not at all Confident", 5 "Somewhat Confident" and 10 "Very Confident"

12. How confident are you in your ability to use the **Internet**?

Not at all Confident — Somewhat Confident — Very Confident

0 1 2 3 4 5 6 7 8 9 10

13. How confident are you that you can use the **Internet** to learn about **exercise**?

Not at all Confident — Somewhat Confident — Very Confident

Turn over to next page →

Using Online Social Networks

14. Do you use social networks like Facebook, Twitter, Patients Like Me or Tumbler? *Please include social network use at home, at work or on a mobile device like a smart phone or tablet computer.*

☐ **YES**

☐ **NO** ⟹ ***If "No" skip to question 18***

15. How many years have you been using the online social networks?

____ years

16. On average, how many total minutes do you spend **each week** using **online social networks** like Facebook, Twitter or MySpace? *Please include social network use at home, at work or on a mobile device such as a smart phone or tablet computer.*

____ minutes (enter "0" if none)

17. How many total minutes do you spend **each week** using the **online social networks** to connect about **exercise**? *Examples include activities like chat rooms, online support groups, online exercise clubs message boards, etc.*

____ minutes (enter "0" if none)

Now please rate your level of confidence, circle one number between 0 and 10. 0 means "'Not at all Confident" and 10 means "Very Confident"

18. How confident are you using **Social Networks** to connect with others?

Not at all Confident — Somewhat Confident — Very Confident

0 1 2 3 4 5 6 7 8 9 10

19. How confident are you using **Social Networks** to **connect** with others about **Exercise**?

Not at all Confident — Somewhat Confident — Very Confident

0 1 2 3 4 5 6 7 8 9 10

Turn over to next page →

Playing Video/Electronic Games

20. Do you play video games? *Please include video games you play at home, at work or on a mobile device such as a smart phone or tablet computer.*

☐ **YES**

☐ **NO** ⟹ ***If "No" skip to question 24***

21. How many years have you been playing video games? ____ **years**

22. On average, how many total **minutes** do you spend **each week** playing **video games** like Nintendo Wii, Xbox or other electronic games? *Please include game playing at home, at work or on a mobile device such as a smart phone or tablet computer.*

____ **minutes (enter "0" if none)**

23. On average, how many total **minutes** do you spend **each week** playing video games to **exercise**? *Examples include Wii Fit, Kinect dancing games.*

____ **minutes (enter "0" if none)**

Now please rate your level of confidence, circle one number between 0 and 10. 0 means "'Not at all Confident" and 10 means "Very Confident"

24. How confident are you playing **Video Games**?

Not at all Confident — Somewhat Confident — Very Confident

0 1 2 3 4 5 6 7 8 9 10

25. How confident are you using **Video Games** to **Exercise**?

Not at all Confident — Somewhat Confident — Very Confident

0 1 2 3 4 5 6 7 8 9 10

Turn over to next page ➔

Using Self-Monitoring Tools

26. Do you use self-monitoring tools to keep track of your health or fitness? *Please include tools like Pedometers, Trackers, GPS fitness trackers like a Garmin or Smartphone Applications.*

☐ **YES**

☐ **NO** ⟹ ***If "No" skip to question 30***

27. How many years have you been using self-monitoring tools? ____ **years**

28. On average, how many total **minutes** do you spend **each week** using self-monitoring tools like, Online Trackers, Food Journals or Smartphone Applications to stay healthy?

____ **minutes (enter "0" if none)**

29. On average, how many total **minutes** do you spend **each week** using self-monitoring tools like Pedometers, Online Trackers, GPS fitness trackers or Smartphone Applications **to track exercise**?

____ **minutes (enter "0" if none)**

Now please rate your level of confidence, circle a number between 0 and 10. 0 means "'Not at all Confident" and 10 means "Very Confident"

30. How confident are you using **Self-Monitoring** devices?

Not at all Confident — Somewhat Confident — Very Confident

0 1 2 3 4 5 6 7 8 9 10

31. How confident are you using **Self-Monitoring** devices to **Track Exercise**?

Not at all Confident — Somewhat Confident — Very Confident

0 1 2 3 4 5 6 7 8 9 10

Turn over to next page ➔

In this section you will be asked questions about exercise and how you feel about exercising

We are interested in the kinds of physical activities that people do as part of their everyday lives. The questions ask about the time you spent being physically active in the **last 7 days**. Please answer questions even if you do not consider yourself to be active. Think about the activities you do at work, as part of house and yard work, to get from place to place, and for recreation, exercise or sport.

Think about all the **vigorous** activities that you did in the **last 7 days**. **Vigorous** physical activities refer to activities that take hard physical effort and make you breathe much harder than normal. Think *only* about those physical activities that you did for at **least 10 minutes at a time**.

32. During the **last 7 days**, on how many days did you do **vigorous** physical activities like heavy lifting, digging, aerobics, or fast bicycling?

_____ **days per week**

☐ No vigorous physical activities → ***Skip to question 34***

33. How much time did you usually spend doing **vigorous** physical activities on one of those days?

_____ **hours per day**

_____ **minutes per day**

☐ Don't know/Not sure

Think about all the **moderate** activities that you did in the **last 7 days**. **Moderate** activities refer to activities that take moderate physical effort and make you breathe somewhat harder than normal. Think only about those physical activities that you did for at least 10 minutes at a time.

34. During the **last 7 days**, on how many days did you do **moderate** physical activities like carrying light loads, bicycling at a regular pace, or doubles tennis? Do not include walking.

_____ **days per week**

☐ No moderate physical activities → ***Skip to question 36***

Turn over to next page →

35. How much time did you usually spend doing **moderate** physical activities on one of those days?

_____ **hours per day**

_____ **minutes per day**

☐ Don't know/Not sure

Think about the time you spent **walking** in the **last 7 days**. This includes at work and at home, walking to travel from place to place, and any other walking that you have done solely for recreation, sport, exercise, or leisure.

36. During the **last 7 days**, on how many days did you **walk** for at least 10 minutes at a time?

_____ **days per week**

☐ No walking → ***Skip to question 38***

37. How much time did you usually spend **walking** on one of those days?

_____ **hours per day**

_____ **minutes per day**

☐ Don't know/Not sure

The last question is about the time you spent **sitting** on weekdays during the **last 7 days**. Include time spent at work, at home and during leisure time. This may include time spent sitting at a desk, visiting friends, reading, or sitting or lying down to watch television.

38. During the **last 7 days**, how much time did you spend **sitting** on a **week day**?

_____ **hours per day**

_____ **minutes per day**

☐ Don't know/Not sure

Turn over to next page →

Confidence Exercising – How confident are you right now that you could engage in **60 minutes** of physical activity **each week** if: **(Circle a number from 0 to 10)**

	Not at all confident				/ Somewhat Confident						Very Confident
39. The weather was bothering you	0	1	2	3	4	5	6	7	8	9	10
40. You were bored by the program or activity	0	1	2	3	4	5	6	7	8	9	10
41. You felt pain when you were exercising	0	1	2	3	4	5	6	7	8	9	10
42. You had to exercise alone	0	1	2	3	4	5	6	7	8	9	10
43. You did not enjoy it	0	1	2	3	4	5	6	7	8	9	10
44. You were too busy with other activities	0	1	2	3	4	5	6	7	8	9	10
45. You felt tired	0	1	2	3	4	5	6	7	8	9	10
46. You felt stressed	0	1	2	3	4	5	6	7	8	9	10
47. You felt depressed	0	1	2	3	4	5	6	7	8	9	10

Now think about the reasons you may not exercise, please indicate whether you agree with the following statements (Circle a number from 1 to 4)

	Strongly Disagree	Disagree	Agree	Strongly Agree
44. Places for me to exercise are too far away	1	2	3	4
45. I am too embarrassed to exercise	1	2	3	4
46. It costs too much money to exercise	1	2	3	4
47. Exercise facilities do not have convenient schedules for me	1	2	3	4
48. I think people in exercise clothes look funny	1	2	3	4

Turn over to next page ➔

Now think about the reasons you may not exercise, please indicate whether you agree with the following statements. (Circle a number from 1 to 4)

	Strongly Disagree	Disagree	Agree	Strongly Agree
49. There are too few places for me to exercise	1	2	3	4
50. Exercise takes too much time from family relationships	1	2	3	4
51. Exercise takes too much time from my family responsibilities	1	2	3	4
52. Exercising takes too much of my time	1	2	3	4
53. Exercise tires me	1	2	3	4
54. I am fatigued by exercise	1	2	3	4
55. Exercise is hard work for me	1	2	3	4
56. My spouse (or significant other) does not encourage exercising	1	2	3	4
57. My family members do not encourage me to exercise	1	2	3	4

Please circle whether or not you agree with each of the following statements about exercise. (Circle a number from 1 to 5)	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
58. Exercise makes me feel better physically	1	2	3	4	5
59. Exercise makes my mood better in general	1	2	3	4	5
60. Exercise helps me feel less tired	1	2	3	4	5
61. Exercise makes my muscles stronger	1	2	3	4	5
62. Exercise is an activity I enjoy doing	1	2	3	4	5
63. Exercise gives me a sense of personal accomplishment	1	2	3	4	5

Turn over to next page →

Please circle whether or not you agree with each of the following statements about exercise. (Circle a number from 1 to 5)	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
64. Exercise makes me more alert mentally	1	2	3	4	5
65. Exercise improves my endurance in performing my daily activities (personal care, cooking, shopping, light cleaning, taking out the garbage)	1	2	3	4	5
66. Exercise helps to strengthen my bones	1	2	3	4	5
67. Exercise makes me more alert mentally	1	2	3	4	5

68. Please tell us anything else you think we should know about electronic health tools.

_____

_____

_____

_____

_____

_____

_____

_____

Thank you for completing this survey! The information you provided will help us understand how you use technology to stay healthy in a whole new way. Please place this completed survey in the self-addressed envelope and send back as soon as you can!

END

APPENDIX B
RECRUITMENT LETTER

Dear Sir or Madam:

The Prevention Plan is pleased to assist Ashley Reynolds in a study of how adults use different types of technology for health. Mr. Reynolds is a doctoral candidate at the University of Florida and Senior Vice President for Health Services at The Prevention Plan. We are supporting this study by sending out a survey.

The enclosed survey has questions about the types of technology you may use, how confident you are about using technology and how you exercise. There are no right or wrong answers. You will not have to answer any question you do not wish to answer. There are questions on the front and back of each page. It should take about 15 minutes to complete. Please complete return the enclosed survey in the enclosed envelope. By completing and returning this survey, you give permission to take part in the study.

The survey is completely anonymous. There is no information that can link your responses to you. U.S. Preventive Medicine, your employer or Mr. Reynolds have no way of knowing whether you have returned the survey. U.S. Preventive Medicine and your employer or insurer will not have access to the study data. Participation will not affect your health insurance or other benefits. If you do not want to take part in the study, do not return the survey. It is completely voluntary. We appreciate your time and support this study.

If you have any questions about this study, please contact Ashley Reynolds at xxx-xxx-xxxx or his faculty supervisor, Dr. Beverly Roberts, who is a professor in the College of Nursing, at xxx-xxx-xxxx. Questions or concerns about your rights as a research participant rights may be directed to the IRB02 office, University of Florida, Box 112250, Gainesville, FL 32611; (xxx) xxx-xxxx.

Paul Risner
EVP - U.S. Preventive Medicine
The Prevention Plan

The Prevention Plan XXXXX Gran Bay Parkway, Suite 2400 Jacksonville, FL 32258 Ph XXX-XXX-XXX
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BIOGRAPHICAL SKETCH

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