Use of Wearable Technology and Social Media to Improve Physical Activity and Dietary
Behaviors among College Students: A 12-week Randomized Pilot Study

A Dissertation
SUBMITTED TO THE FACULTY OF
UNIVERSITY OF MINNESOTA
BY

Zachary Clark Pope

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

Zan Gao, Ph.D.

June 2018

Acknowledgements

To begin, I would like to give a heartfelt thanks to my main advisor, Dr. Zan Gao. Indeed, I have been truly blessed by his extraordinary mentorship over the last four years and the opportunities that he has provided me to grow my skills and expand my knowledge within the field of physical activity and health. Dr. Gao has acumen for discerning the abilities of his mentees and assisting them in the pursuits that most interest them. Without him, I would not be where I am today.

Second, I would like to thank my dissertation committee members, Drs. Beth Lewis, Daheia Barr-Anderson, and Mark Pereira. Specifically, Drs. Beth Lewis and Daheia Barr-Anderson were outstanding in their mentorship within the areas of behavioral change theory and intervention design. Both have tremendous reputations within the field of Kinesiology and beyond, and the help they provided me while I designed and implemented my dissertation is a testament to the preceding fact. Further, I would like to thank Dr. Mark Pereira for his mentorship and expertise in both physical activity and nutritional epidemiology. My dissertation benefitted greatly from his continued insight. To say he has done a lot within the field of public health is an understatement, and I look forward to working with Dr. Pereira during my postdoctoral fellowship. Undoubtedly, I cannot wait to collaborate with all four committee members during my future career.

Third, I would also like to thank fellow research assistants Jung Eun Lee and Nan Zeng within the Physical Activity Epidemiology Laboratory. No matter the time or distance that passes, both individuals will be lifelong friends and collaborators, with Jung

and Nan contributing mightily to my education and experience at the University of Minnesota. Relatedly, I thank the amazing faculty/staff within the School of Kinesiology as well as my fellow peers for all the support they have provided me these last four years.

Finally, I want to thank my wife, Christiana, my Dad, Mom, and Sister, and my wife's Family for the support they have provided me as I have worked toward obtaining my doctorate. Their prayers, encouragement, and belief in my abilities have meant more to me than I can fully express. As a final and exceedingly important note, I would like to thank my Lord and Savior Jesus Christ for the strength, focus, mindset, and circumstances which had to occur to ensure completion of this dissertation. No, the ride has not been and will likely never be easy, but I know with Him I am in the best of hands.

Dedication

This dissertation is first and foremost dedicated to my wife, Christiana, my parents, Clark and Debbie, and my sister, Shelbie. Additionally, I dedicate this dissertation to the Raymond Family—Cliff, Marcia, Jonathan, Seth, and Brittany.

Abstract

Introduction: Two-thirds of U.S. adults are overweight or obese presenting numerous physiological and economic consequences. Physical inactivity and poor dietary habits are often cited as major contributing factors to the high overweight/obesity prevalence observed. The ubiquitous nature of modern-day technology has led to investigations of technology-based health behavior change interventions, with smartwatches among the most popular technologies given these devices' capabilities to track daily activity time, steps per day, and energy expenditure, among other health metrics. College students are at risk for overweight and obesity due to stressors common to college attendance. Indeed, high physical inactivity prevalence and poor dietary behaviors are observed in this population. Yet, present-day college students are technology-savvy and familiar with the use of smartwatches while also frequently using social media sites such as Facebook. Moreover, investigation of smartwatch data validity and reliability in free-living conditions is understudied. Therefore, this study's purpose was two-fold: (a) evaluate the effectiveness of the Polar M400 smartwatch in combination with a Social Cognitive Theory- and Self-Determination Theory-based, Facebook-delivered health education intervention at promoting improved physical activity, physiological, psychosocial, and dietary outcomes among college students versus comparison over 12 weeks; and (b) examine the validity, precision/bias, and reliability of the Polar M400 smartwatch's health metric data compared to the research-grade ActiGraph Link accelerometer.

Methods: Thirty-eight college students from a large metropolitan research University in the Midwest participated in this two-arm randomized 12-week pilot trial during Fall 2017 and Spring 2018. Participants were initially screened for inclusion after which they were randomized into two groups: (a) experimental group – received the Polar M400 and a twice-weekly Social Cognitive Theory- and Self-Determination Theory-based, Facebook-delivered health education intervention; and (b) comparison group – enrolled only in a separate, but content-identical, Facebook group. Changes in college students' sedentary behavior, light physical activity, and moderate-to-vigorous physical activity durations as well as steps per day were measured using the ActiGraph Link accelerometer while dietary changes were measured using the National Cancer Institute's Automated Self-Reported 24-Hour (ASA24) Food Recall. These measurements were completed at baseline, 6 weeks, and 12 weeks. Finally, a battery of psychometrically-validated questionnaires was administered at baseline and 12 weeks to evaluate changes in Social Cognitive Theory- and Self-Determination Theory-related psychosocial constructs, with weight, body fat percentage, and cardiorespiratory fitness measured at the same time points. Baseline comparisons were completed for continuous and categorical variables using independent *t*-tests and chi-square tests, respectively. A series of repeated measures ANOVAs (within-subjects factor: time; between-subjects factor: group) examined differences between groups over time in objectively-measured physical activity levels and self-efficacy, social support, enjoyment, barriers, outcome expectancy, and intrinsic motivation in addition to cardiorespiratory fitness, body composition, and dietary behaviors. Quantitative use/acceptability data was evaluated descriptively, with

qualitative use/acceptability data examined via thematic analysis. The validity, precision/bias, and reliability of the Polar M400's daily activity time and steps per day metrics were evaluated against that of the ActiGraph Link. Specifically, validity was assessed using intraclass correlation coefficients and dependent *t*-tests while precision/bias was examined using coefficients of variation and Bland-Altman plots with follow-up linear regression. Reliability was evaluated via calculation of test-retest reliability. Alpha was 0.05 for all analyses.

Results: Three experimental group participants discontinued participation for reasons unrelated to the study (retention rate = 92.1%). These participants' baseline data were not significantly different from completers; thus, an intent-to-treat analysis was performed. Baseline comparisons revealed only one significant difference between groups for whole grain consumption, $t = 2.3$, $p = 0.03$, as the experimental group had higher whole grain consumption than the comparison group. Overall, however, baseline comparisons suggested adequate randomization procedures. While no significant interaction or main effects were observed for moderate-to-vigorous physical activity, light physical activity, sedentary behavior, or steps per day, a trend toward a significant main effect for time was observed for moderate-to-vigorous physical activity, $F(2, 72) = 2.6$, $p = 0.08$; $\eta_p^2 = 0.07$, with the experimental and comparison groups demonstrating 4.2- and 1.6-minute increases, respectively, from baseline to six weeks. Although both groups demonstrated slightly decreased moderate-to-vigorous physical activity from the six weeks to 12 weeks, the mean duration for both groups was still higher than observed at baseline and

not significantly lower than observed at six weeks ($p > 0.05$). For secondary outcomes, observations indicated a significant main effect for body fat percentage, $F(1, 36) = 5.8$, $p = 0.02$; $\eta_p^2 = 0.14$, such that both groups had increased body fat percentage over time (experimental: 2.2%-increase; comparison: 0.3%-increase). Interestingly, however, both groups demonstrated non-significantly decreased weight from baseline to 12 weeks (experimental: -0.6 kg; comparison: -0.5 kg). Regarding cardiorespiratory fitness, the comparison group was observed to have slightly improved cardiorespiratory fitness over time, with the experimental group demonstrating somewhat decreased cardiorespiratory fitness over the same period. Although no interaction effects for group over time were observed for any psychosocial outcomes, significant main effects for time were observed for self-efficacy, $F(1, 36) = 22.5$, $p < 0.01$; $\eta_p^2 = 0.38$, social support, $F(1, 36) = 8.0$, $p < 0.01$; $\eta_p^2 = 0.18$, and intrinsic motivation, $F(1, 18) = 14.2$, $p < 0.01$; $\eta_p^2 = 0.28$, such that both groups improved significantly on these outcomes from baseline to 12 weeks.

Further, trends toward significant main effects for time were observed for enjoyment, $F(1, 36) = 3.9$, $p = 0.06$; $\eta_p^2 = 0.10$, outcome expectancy, $F(1, 36) = 3.3$, $p = 0.08$; $\eta_p^2 = 0.09$, and barriers, $F(1, 36) = 3.4$, $p = 0.07$; $\eta_p^2 = 0.09$. In detail, both groups experienced improved enjoyment and outcome expectancy, with reduced barriers, from baseline to 12 weeks. Finally, analyses of dietary outcomes revealed a significant interaction effect for sugar-sweetened beverage consumption amount (in cups), $F(2, 24) = 5.8$, $p < 0.01$; $\eta_p^2 = 0.33$, with, predictably, a significant interaction effect also observed for sugar-sweetened beverage consumption kcalories, $F(2, 24) = 3.9$, $p = 0.03$; $\eta_p^2 = 0.25$. Specifically, the

experimental group significantly increased the amount and kcalories consumed from sugar-sweetened beverages versus comparison from baseline to six weeks. Notably, however, both groups had sugar-sweetened beverage consumption amount and kcalories at 12 weeks which were approximately equal to or lower than that observed at baseline. While no other interaction or main effects were observed for dietary outcomes, two other noteworthy observations were made for dietary outcomes. First, trends toward significant interaction effects for group over time were observed for vegetable consumption including legumes, $F(2, 72) = 2.9, p = 0.06; \eta_p^2 = 0.07$, and, unsurprisingly, vegetable consumption excluding legumes, $F(2, 72) = 2.8, p = 0.07; \eta_p^2 = 0.07$. Specifically, the comparison group demonstrated slight increases in these two outcomes from baseline to six weeks while the experimental group demonstrated little to no change. However, at 12 weeks the comparison group had experienced decreased vegetable consumption including and excluding legumes to values below that observed at baseline, with the experimental group having remained stable over time. Second, it is notable that both groups demonstrated consistently decreased caloric consumption from baseline to six weeks to 12 weeks (overall decreases - experimental: -41.0 kcalories; comparison: -143.3 kcalories). Intervention use/acceptability revealed high adherence to the Facebook-delivered health education intervention (experimental: $89.8 \pm 21.8\%$; comparison: $84.4 \pm 22.3\%$), with both groups reporting the health education intervention to be “somewhat helpful” and most participants implementing the health education tips between “two times per month” and “one to three times weekly”. Notably, experimental group participants reported the Polar M400 to be “somewhat useful” to “useful” for assisting

them in becoming more active and stated the smartwatch to be “somewhat easy” to use, with the most frequently reported positive and negative features of the device reported as the “exercise bar” on the main screen and the difficult smartphone syncing process, respectively.

Intraclass correlation coefficients for the association between the Polar M400’s daily activity time and steps per day measurements and the same health metrics from the ActiGraph Link were strong at 0.64 and 0.72, respectively. Subsequent dependent *t*-tests indicated marginal validity for the Polar M400’s steps per day measurements, $t = 1.9$, $p = 0.08$, but not daily activity time, $t = -9.4$, $p < 0.01$. Further, little measurement bias was observed for the Polar M400’s daily activity time measurements, with a follow-up linear regression corroborating this observation, $F(1, 18) = 1.0$, $p = 0.34$. However, it is noteworthy that the Polar M400 consistently overestimated daily activity time, with wide limits of agreement observed for this overestimation (95% CI: -6.5, -129.9 minutes; ActiGraph Link was reference so negative CI indicates overestimation by Polar M400). Some measurement bias was observed for the Polar M400’s steps per day measurements such that when lower steps per day were accrued, the device more greatly underestimated this metric. This observation was confirmed with a significant linear regression analysis, $F(1, 18) = 8.4$, $p = 0.01$, as well as limits of agreement more pronounced for underestimation (95% CI: 4,211.3, -2689.5; ActiGraph Link was reference so more positive CI indicates underestimation by Polar M400). Moreover, coefficients of variation suggested the Polar M400 had moderate precision for daily activity time measurements, but poor precision for steps per day measurements. Finally, the Polar M400 demonstrated

poor test-retest reliability for daily activity time ($r = 0.15$, $p = 0.55$) but possessed moderate test-retest reliability for steps per day ($r = 0.54$, $p = 0.02$).

Discussion: Observations of the current study indicated that an intervention combining the use of a smartwatch and theoretically-grounded, social media-delivered health education intervention may not provide much greater benefit than a standalone theoretically-based, social media-delivered health education intervention for improving college students' health outcomes. Yet, the improvements for moderate-to-vigorous physical activity, weight, and psychosocial constructs among both groups are promising. Indeed, these observations suggested that a low-burden, well-integrated approach to health behavior change akin to that employed may be able to be scaled for use on bigger platforms among more diverse populations. More in-depth nutrition education might be provided during future interventions of this type, however. Finally, validation of the Polar M400 versus the ActiGraph Link suggested the smartwatch to have moderate validity and reliability for steps per day, with poor validity and reliability observed for this device's daily activity time measurements. Therefore, caution is suggested if using the Polar M400 to develop health behavior change programs wherein highly accurate physical activity time measurements are vital (e.g., clinical weight loss programs). Future studies should include a larger/more heterogeneous sample, discern a way by which to limit the confounding effect of academic school year breaks (e.g., Thanksgiving/Christmas breaks, spring break, and summer break) on intervention outcomes, and consider using a delayed-intervention control group.

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Chapter One: Introduction

Approximately 68% of U.S. adults are overweight or obese (Ogden, Carroll, Fryar, & Flegal, 2015). While factors contributing to overweight and obesity among adults are complex and multi-faceted, among the biggest culprits are high physical inactivity rates and poor dietary habits. Specifically, research (Troiano et al., 2008; World Health Organization [WHO], 2016) has indicated that as few as five-percent of U.S. adults are meeting the national physical activity recommendations of 30 minutes of moderate-intensity physical activity daily on $\geq$ five days per week (Physical Activity Guidelines Advisory Committee [PAGAC], 2018; U.S. Department of Health and Human Services [USDHHS], 2008). Further, recent data indicate that over 30% of U.S. adults are completely physically inactive (PAGAC, 2018). Keeping the preceding facts in mind, high overweight and obesity prevalence is unsurprising given continued progressively higher daily caloric consumption reported over the last few decades (Centers for Disease Control and Prevention [CDC], 2004; Giskes, van Lenthe, Avendano-Pabon, & Brug, 2011)—an increase derived mostly from calorie-dense, nutrient-deprived foods like sugar-sweetened beverages, junk and/or highly processed foods, etc. which contribute to a positive energy balance and weight gain over time. Notably, overweight and obesity are major factors in the development of non-communicable chronic diseases such as cardiorespiratory disease, cancer, respiratory disease, and diabetes (WHO, 2011), with overweight and obese individuals having higher disease risks than normal weight individuals (American Heart Association, 2015; Field et al., 2001; USDHHS, 2010). Treatment of these non-communicable diseases also results in economic consequences,

with data suggesting nearly a quarter of annual U.S. medical costs is attributable to obesity-related non-communicable chronic diseases (Cawley & Meyerhoefer, 2012; WHO, 2011). Thus, a need exists to investigate novel health behavior change strategies which might be able to effect change in population-level physical activity and dietary behaviors.

Given the ubiquitous nature of modern technology, researchers have been investigating and advocating for the use of technology in the development and implementation of health behavior change interventions (Nigg, 2003; Welch et al., 2018). Social media, smartphone applications, and wearable technology are among several technologies being investigated for their ability to promote positive health behavior change, with smartwatches—a form of wearable technology—currently situated in a hot and growing area of health behavior change research (Henriksen et al., 2018; Muller et al., 2018). Interest in using smartwatch technology to promote health behavior change lies in these devices' popularity among consumers—particularly younger, tech-savvy individuals. Indeed, smartwatches allow individuals to track health metrics like steps per day, energy expenditure, activity time, and sleep after which these health metrics can be transferred via Bluetooth to an associated smartphone application or internet-based portal allowing users to analyze these data and modify health behaviors (Schembre et al., 2018; Zeng & Gao, 2017). Therefore, using smartwatches as a component of health behavior change interventions may assist individuals in learning how to better self-regulate (i.e., track and modify) health behaviors in a manner conducive to improved health.

Of the paucity of high-quality randomized studies to date on the use of

smartwatches to promote health behavior change, findings have been mixed. Briefly, a series of studies observed smartwatch use facilitated increased physical activity among overweight and obese women versus control (Cadmus-Bertram, Marcus, Patterson, Parker, & Morey, 2015a, 2015b), with another study by Thorndike et al. (2014) among medical residents showing slightly increased physical activity participation compared to control. Other studies, however, have cited no effect of smartwatch use on physical activity participation among overweight and obese adults (Wang et al., 2015) and have even observed slightly decreased physical activity among older adults using a smartwatch to track personal physical activity levels (Thompson, Kuhle, Koepp, McCrady-Spitzer, & Levine, 2014). Yet, it is important to note the limitations present within this literature which may have contributed to these mixed observations.

First, the randomized studies conducted to date have not employed any theoretical framework to guide the development and implementation of the health behavior change intervention. This is a limitation as use of behavior change theory—for example, the Social Cognitive Theory (Bandura, 1977, 1986) and Self-Determination Theory (Ryan & Deci, 2000)—has been indicated to facilitate increased intervention effectiveness (Brug, Oenema, & Ferreira, 2005; Glanz & Rimer, 2005). Second, standardized intervention fidelity protocol was only reported in one study (Cadmus-Bertram et al., 2015b). Among several reasons, employing intervention fidelity protocol is vital to ensure participants adhere to the health behavior change intervention—possibly leading to increased intervention effectiveness (Borrelli, 2011). Third, no study included a health education component. Health education is important if researchers and health professionals desire to

increase health literacy among participants/clients—skills/knowledge necessary to assist individuals in participating in beneficial long-term health behaviors (Nielsen-Bohlman, Panzer, & Kindig, 2004; Rikard, Thompson, McKinney, & Beauchamp, 2016). As such, perhaps using a social media platform to deliver health education to participants would be worthwhile given this platform’s widespread integration into the daily lives of most individuals—particularly within the U.S. (Pew Research Center, 2017). Finally, no nutritional component was included within the preceding health behavior change interventions. Research has indicated, however, that health behavior change interventions concentrating concurrently on improving physical activity and dietary behaviors are more effective than interventions concentrating on either of these behaviors exclusively (Elliot & Hamlin, 2018; Kohl III & Murray, 2012a). Future health behavior change interventions should look to build upon these limitations when examining how smartwatch use in combination with health education—the latter delivered via social media—might improve individuals’ physical activity and dietary behaviors.

Rationale

College students represent a population which might benefit from a theoretically-grounded health education intervention which combines the use of a smartwatch and social media platform to facilitate improved physical activity and dietary behaviors. In fact, data has suggested that college students demonstrate high levels of physical inactivity and overweight/obesity (Nelson, Gortmaker, Subramanian, Cheung, & Wechsler, 2007; Peterson, Sirard, Kulbok, DeBoer, & Erickson, 2018; Sira & Pawlak, 2010) in addition to poor dietary behaviors (e.g., high sugar-sweetened beverage

consumption, low intake of fruits and vegetables and foods and whole grains) (Larson, Neumark-Sztainer, Story, & Burgess-Champoux, 2010; Racette, Deusinger, Strube, Highstein, & Deusinger, 2005). This poorer engagement in health-enhancing behaviors has been attributed to college students newfound autonomy and responsibility of balancing school, work, social, and health demands after beginning college (Deliens, Deforche, De Bourdeaudhuij, & Clarys, 2015; Desai, Miller, Staples, & Bravender, 2008).

Only three randomized trials have investigated the use of smartwatches in the promotion improved health behaviors among college students. Specifically, Kim, Lumpkin, Lochbaum, Stegemeier, and Kitten (2018) and Melton, Buman, Vogel, Harris, and Bigham (2016) investigated whether smartwatch use among college students might promote increased physical activity participation, with both studies reporting no effect of smartwatch use on physical activity over time compared to control. In a third study by Rote (2017), significantly increased steps per day were indicated from pre- to post-intervention when assessed by the study-related pedometer—an observation not made in the study’s comparison and control groups. It is noteworthy, however, that when these researchers examined the experimental group’s Fitbit data, a decrease of nearly 2,500 steps per day was observed over the course of the intervention—adding skepticism to the findings. All three studies had limitations worth noting which might assist in discerning why little to no effect was observed—some not too different from those listed above for studies conducted in other populations.

First, no study made explicit use of any established health behavior change theory

or evaluated changes in any physiological (e.g., weight, body fat percentage, cardiorespiratory fitness), psychosocial (e.g., self-efficacy, social support, enjoyment, outcome expectancy, barriers, intrinsic motivation), or dietary (e.g., sugar-sweetened beverage consumption; intake of fruits, vegetables, and whole grains) outcomes. Further, while Kim and colleagues (2018) did include intervention fidelity protocol, this protocol was only implemented once during the 15-week intervention suggesting that more frequent intervention fidelity measures may be needed to ensure adequate intervention adherence and effectiveness—particularly among college students with several constraints on their time. Finally, while a health education component was included in the studies by Kim and colleagues (2018) and Rote (2017), these educational components focused mainly on physical activity despite the previously referenced importance of including nutrition education in health behavior change interventions. Further, it is noteworthy that the health education component included in both studies were college courses—limiting the future generalizability of these researchers’ interventions to only those attending college. Recent research (Welch et al., 2018), however, has advocated for the use of social media in health behavior change interventions given the technology’s ability to reach large groups of people regardless of their race/ethnicity and place of residence (e.g., urban versus rural living), among other advantages like the increased generalizability/scalable nature of this framework and the reduced burden this framework places on individuals to travel to a health center or clinic.

College students are technology-savvy and connected, with recent surveys indicating 90% of college students currently use at least one social media site and

comprise the large proportion of Facebook users—many accessing the site multiple times daily (Perrin, 2015). Moreover, literature indicates college students and, more generally, young adults, to be interested in the use of technology for health promotion purposes (Partridge & Redfern, 2018). Thus, this population may present an ideal cohort among which to investigate the effectiveness of a combined smartwatch-based and theoretically-grounded, social media-delivered health education intervention. Not only would this type of investigation have implications pertinent to improving college student health but, if found feasible and effective, this methodology could be scaled and translated to other community-based and clinical populations.

Specific Aims and Hypotheses

The purpose of this 12-week pilot randomized trial was two-fold. First, the study investigated the effectiveness of the Polar M400 smartwatch, used in combination with a twice-weekly Social Cognitive Theory- and Self-Determination Theory-based, Facebook-delivered health education intervention, in the promotion of more healthful physical activity and dietary behaviors over 12 weeks in college students versus a comparison group. Second, given the fact that the validity and reliability of the health metric data smartwatches provide is understudied in free-living settings (Bunn, Navalta, Fountaine, & Reece, 2018; Evenson, Goto, & Furberg, 2015), the study's second purpose was to evaluate the validity, precision/bias, and reliability of the Polar M400 in the assessment of free-living (i.e., non-laboratory based) daily activity time and steps per day. In detail, the following specific aims and associated hypotheses were proposed:

Aim 1. Determine the effectiveness of the Polar M400, in combination with a

twice-weekly Social Cognitive Theory- and Self-Determination Theory-based, Facebook-delivered health education intervention on college students' physical activity behaviors in addition to this cohort's physiological, psychosocial, and dietary outcomes over 12 weeks versus comparison. Based upon the study's first aim, the following hypotheses were developed.

Hypothesis 1. Experimental group participants receiving both the Polar M400 and theoretically-grounded, Facebook-delivered health education intervention will have greater improvements in objectively-assessed moderate-to-vigorous physical activity, light physical activity, and steps per day in addition to larger decreases in sedentary behavior over 12 weeks versus comparison participants enrolled only in a separate, but content identical, Facebook-delivered health education intervention.

Hypothesis 2. Experimental group participants will demonstrate more favorable changes in weight, body composition, and cardiorespiratory fitness over 12 weeks versus comparison participants.

Hypothesis 3. Experimental group participants will demonstrate greater improvements in self-efficacy, social support, enjoyment, outcome expectancy, and intrinsic motivation as well as greater reductions in barriers over 12 weeks versus comparison—constructs aligned with the Social Cognitive Theory and Self-Determination Theory.

Hypothesis 4. Experimental group participants will demonstrate more nutritious eating behaviors (i.e., increased fruit, vegetable, and whole grain consumption; decreased daily caloric intake and sugar-sweetened beverage consumption) than comparison

participants over 12 weeks.

Aim 2. Determine the validity, precision/bias, and reliability of the Polar M400's health metric data in free-living conditions through the comparison of this smartwatch's data output with that of a research-grade ActiGraph Link accelerometer. The following hypothesis was proposed for this study's second aim.

Hypothesis 1. In comparison to a research-grade Actigraph Link accelerometer, the Polar M400's health metrics for daily activity time and steps per day will be observed as moderately valid and reliable, with adequate precision and little bias during free-living conditions.

Summary

Overweight and obesity prevalence is strikingly high, with physical inactivity and poor dietary behaviors major contributory factors. As overweight and obesity has numerous physiological and economic consequences, novel health behavior change strategies capable of improving population-level participation in healthier behaviors are needed. Combining smartwatch use with a social media platform may be an effective method by which to deliver theoretically-grounded health education interventions to large populations of people in a manner well-integrated into modern-day life—particularly if smartwatch health metric data is valid, precise, and reliable and participants adhere sufficiently to the social media-based health education intervention. Therefore, should the observations of this study indicate that a combined smartwatch and theoretically-grounded, social media-based health education intervention is effective at promoting improved physical activity behaviors, physiological/psychosocial health, and more nutritious eating behaviors, this model may serve as a scalable manner by which to deliver future health education interventions to more diverse populations. Additionally, should the Polar M400 smartwatch employed in this study be observed to provide valid, precise, and reliable health metric data with little measurement bias, these observations would provide a viable smartwatch option for consumers and health professionals alike which provides health metric data accurate enough for the development of health and wellness programs.

Chapter Two: Literature Review

The following literature review will discuss in detail the information provided concisely within the introduction. Specifically, the following will be included within this section: (a) factors contributing to overweight and obesity and the associated health and economic consequences; (b) technology integration within health behavior change interventions, with specific concentration on smartwatch technology, the current findings/limitations of the present literature on these devices within health behavior change interventions, and the latest validation studies of these devices' health metric data; (c) two prominent health behavior change theories—namely, the Social Cognitive Theory (Bandura, 1977, 1986) and Self-Determination Theory (Ryan & Deci, 2000)—and these theories' constructs and use within the health behavior change literature, with greater concentration placed on these theories' use within health behavior change interventions among young adults/college students; and (d) health concerns among college students and the rationale for theoretically-grounded, technology-based implementation of health behavior change interventions to improve physical activity and dietary behaviors among this population.

Contributory Factors for Overweight/Obesity and Associated Consequences

Presently, just over two-thirds of U.S. adults are overweight *or* obese, with rates of obesity increasing from approximately 15% in 1980 (Finkelstein, Ruhm, & Kosa, 2005) to 36.5% in 2014 (Ogden et al., 2015). Physical inactivity has been cited as a contributory factor in the preceding increase (PAGAC, 2018). Large scale studies utilizing

accelerometry to investigate the percentage of participants achieving the recommended 30 minutes of moderate-intensity physical activity daily on $\geq$ five days per week (Haskell et al., 2007; PAGAC, 2018; USDHHS, 2008) have shown that approximately five-percent of U.S. adults meet these recommendations (Troiano et al., 2008), with 30% of U.S. adults completely physical inactive (PAGAC, 2018). Additionally, easier access to fast-food and less access to supermarkets as well as greater consumption of energy-dense, fatty foods and sugar-sweetened beverages are also major contributing factors (Giskes et al., 2011; Larson et al., 2010), with Americans' daily energy intake increasing by 200-300 kcalories in the last few decades (Centers for Disease Control and Prevention [CDC], 2004). Relatedly, Americans are not eating lower-kcalorie, nutrient-dense foods. For example, the most recent CDC report (see Moore & Thompson, 2015) on average fruit and vegetable intake indicated only 13.1% and 8.9% of Americans eat the recommended daily amount of two cups of fruit and three cups of vegetables, respectively (U.S. Department of Agriculture [USDA], 2015). Moreover, research utilizing National Health and Nutrition Examination Survey data (McGill, Fulgoni III, & Devareddy, 2015) has indicated American men and women rarely meet the recommended six- and eight-ounce equivalent servings, respectively, for daily whole grain intake (USDA, 2017). These are notable observations as insufficient physical activity and increased kcaloric consumption heighten the likelihood of a positive energy balance and subsequent weight gain over time, with higher overweight and obesity prevalence at the population-level having health and economic consequences.

Physiologically, it is well known that individuals who are overweight or obese have

significantly higher risks versus healthy weight individuals for the development of gallstones, diabetes, hypertension, coronary heart disease, colon cancer, and, for men, stroke incidence (Field et al., 2001; USDHHS, 2010). Further, the WHO (2011) has stated non-communicable diseases (cardiovascular disease, cancer, respiratory disease, diabetes) are largely preventable given that non-communicable disease risk factors often demonstrate positive associations with overweight and obesity/excess body fat. In fact, weight reduction is consistently cited as important in reducing risk of cardiovascular disease (PAGAC, 2018; USDHHS, 2010), with reductions in weight (approximately 10% of total body weight) observed to reduce systolic and diastolic blood pressure 7 mmHg and 5 mmHg, respectively (Franz, Boucher, Rutten-Ramos, & VanWormer, 2015; Neter, Stam, Kok, Grobbee, & Geleijnse, 2003). Aside from health benefits weight reduction confers, reduced body fat percentage—particularly among individuals with android body fat distribution (i.e., fat accumulation around the midsection)—is also important (Kenney, Wilmore, & Costill, 2015b). Indeed, android fat is more metabolically-active and likely to be observed viscerally than gynoid fat (i.e., fat accumulation around the hips/thighs)—increasing the risk of various diseases such as diabetes and cardiovascular disease (Despres, 2012) as well as cancer and all-cause mortality (Britton et al., 2013). Regarding economic consequences, the most recent large-scale estimates on medical costs associated with obesity-related diseases and illnesses stated that approximately one-quarter of annual U.S. medical care expenditures are attributable to treatment of these conditions, equating to annual expenditures approaching \$500 billion USD (Cawley & Meyerhoefer, 2012; WHO, 2011). As such, preventing overweight and obesity in the U.S.

is vital not only to ensure healthy citizens but also a strong economy.

Technology has become ubiquitous in everyday life. Therefore, the implementation of innovative technology-based health behavior change interventions which strive to increase physical activity and promote nutritious eating behaviors might present a viable manner by which to attenuate the increases in overweight and obesity and prevalence of non-communicable diseases while facilitating healthier lifestyles across the life span—particularly when implemented among younger populations.

Technology Integration in Health Promotion

Technology has become an inseparable part of life in the 21st century, largely as a result of the increasingly globalized economy and the need for quick, efficient communication (Buchanan, 2016). Given the omnipresence of technology, researchers have experimented with the use of technology for health promotion. While computers and other internet-based platforms have been used for health promotion (Nigg, 2003), social media, smartphone apps, and wearable technology are currently of great interest to aid in the cost-effective, efficient delivery of health behavior change interventions. Indeed, given the latter three technologies' capabilities to assist in educating individuals on proper health behaviors and in the self-regulation of health behaviors congruent with better health (e.g., physical activity participation, nutritious eating behaviors [indirectly via the tracking of energy expenditure]) researchers are more often advocating their use in health behavior change interventions (Bunn et al., 2018; Henriksen et al., 2018; Muller et al., 2018; Welch et al., 2018). Wearable technologies, a popular form of modern-day technology, may hold great promise for promoting health behavior change.

Ranging in price from \$100-250 USD, wearable technology aids users in improving health behaviors by tracking—via internal sensors—various health metrics such as step counts, activity time, stairs climbed, calories burned (i.e., energy expenditure), and sleep, among other metrics (Almalki, Gray, & Sanchez, 2015). Wearable technology has seen increasing popularity among consumers—representing an approximately \$4 billion market in 2015 with projected market growth to nearly \$10 billion in 2019 (Statista, 2016a). Current wearable technologies available to consumers include, but are not limited to: smart belts such as Samsung’s Wellness Belt (WELT; Statt, 2016); Hexoskin’s Biometric Shirt (Hexoskin, 2016); Wisewear’s Smart Jewelry (Wisewear, 2016); and a diverse array of smartwatches from companies such as Polar, Fitbit, Apple, Jawbone, and Pebble. Regardless of the wearable technology’s design, most devices are capable of wirelessly uploading health metrics onto smartphone application-based and/or internet-based portals. Nonetheless, the ability to monitor these health metrics is important as it can facilitate the user’s self-regulation of health behaviors as the user tracks progress toward personal health goals in addition to possibly receiving social support from friends already using the device’s internet portal or smartphone application (Lyons, Lewis, Mayrsohn, & Rowland, 2014). Moreover, given most devices’ capability to track energy expenditure, an individual may also adjust caloric intake based upon the energy expenditure readings provided by wearable technology devices. Smartwatches are arguably the most popular and widely available wearable technology among consumers.

Smartwatch Technology

The founding of Fitbit in 2007 and the subsequent release of the Fitbit Classic acted

as the impetus for the ever-growing smartwatch market (Fitbit, 2016), with other companies following suit and beginning to devote considerable attention to the research and development of smartwatch devices. Polar, a long-standing name within health and wellness technology, is a company currently positioning themselves to compete against other technology companies (e.g., Apple, Fitbit, Jawbone, Pebble, etc.) vying for smartwatch supremacy. Specifically, Polar has released a line of powerful no-frills smartwatches offering global positioning system (GPS) capabilities and Bluetooth compatibility. Among the most popular Polar smartwatches is the Polar M400 (Polar, 2017).

The Polar M400 can upload health metric data to an associated smartphone application and internet portal regarding the user's steps per day; time spent lying down, sitting, and standing; durations of moderate and vigorous physical activity; daily activity time; energy expenditure; and sleep. Moreover, akin to other popular smartwatches, the Polar M400 is capable of alerting users to incoming phone calls, text messages, calendar notifications, and social media alerts (Polar, 2017). Yet, despite the Polar M400's competitive features and Polar's strong reputation within the field of health and wellness technology, the recent introduction of Polar's smartwatch technology has meant no known research has been conducted on: (a) the ability of the Polar M400 to promote positive behavior change within the context of a health intervention; and (b) the validity and reliability of the Polar M400 compared to wrist-mounted research-grade accelerometers like the ActiGraph Link. Investigations into the preceding points are necessary given the increasing use of smartwatches within health behavior change

interventions in community- and clinically-based settings.

Smartwatch Use in Health Behavior Change Interventions

Only a paucity of high-quality, randomized studies have been completed on the use of smartwatches or other wrist-bound devices in health behavior change interventions. Most concentration has been on the use of different models of the Fitbit in populations such as older adults (Thompson et al., 2014), overweight and obese populations (Cadmus-Bertram et al., 2015a, 2015b; Wang et al., 2015), and adults (Thorndike et al., 2014). Observations from these studies have been mixed. For instance, Cadmus-Bertram et al. (2015a, 2015b) observed significantly increased moderate-to-vigorous physical activity and steps per day over 16 weeks among overweight and obese postmenopausal women compared to non-significant increases during the intervention among controls, with no significant decline in use over time—an important observation when striving to promote long-term behavior change given the need for intervention adherence (Borrelli, 2011). Conversely, studies by Wang et al. (2015), Thompson et al. (2014), and Thorndike et al. (2014) did not find such positive results. Wang et al. (2015) found provision of a Fitbit and text-messaging prompts to promote increased physical activity among overweight and obese adults *only* during the first week of the study, with Thorndike et al. (2014) observing only slightly increased physical activity among medical residents provided a Fitbit during a 12 week intervention versus control. Finally, Thompson et al. (2014) observed decreased physical activity compared to control among older adults provided exercise counseling and a Fitbit to track physical activity levels.

The above findings demonstrate mixed agreement with a review of the

effectiveness of accelerometer-based wearable technology used in health behavior change interventions conducted by Goode et al. (2017). In detail, across all studies, small but significant positive effects were observed when using wearable technology to promote physical activity and weight loss—the latter likely promoted because of the wearable technology assisting to increase physical activity participation and as individuals modified caloric consumption based upon energy expenditure data provided by these devices. It is notable, however, that while some wearable technologies in the preceding review were smartwatches, other devices were worn at the waist—the latter devices differing from smartwatches like the Polar M400 and preventing a true review of the effectiveness of smartwatch technology use within health behavior change interventions. Regardless, despite the mixed agreement of the preceding literature with this recent review, at least four limitations are present among the literature which might explain these studies' observations.

First, little mention was made of the use of any type of theoretical framework to guide intervention design and implementation. While a fuller discussion of theory will be presented later in this literature review, theory-based intervention design and implementation is vital to facilitate researchers' increased ability to more effectively target determinants of health behaviors (Brug et al., 2005; Glanz & Rimer, 2005) and interpret observations of an intervention (Patten, 2014). Second, intervention fidelity was lacking as only one study (Cadmus-Bertram et al., 2015a) reported any type of procedures used to gauge participants' adherence to intervention protocol. While intervention fidelity includes several components besides the monitoring of participant

intervention protocol adherence (Borrelli, 2011; Kohl III & Murray, 2012b), periodically prompting participants to engage in intervention protocol can increase intervention effectiveness. Third, no study included any type of structured health education piece. This is notable as the promotion of improved health literacy has been highlighted (Nielsen-Bohlman et al., 2004), with health education important to ensure individuals have the baseline skills/knowledge to engage in proper health behaviors in the long-term (i.e., after participation in a program or intervention concludes) (Cha et al., 2014; Rikard et al., 2016). Finally, a greater concentration on nutrition might be necessary during intervention delivery. Although Thorndike et al. (2014) did provide participants the option to participate in nutritional counseling, this was not a required intervention component, with few participants reportedly taking advantage of this option. As combined physical activity and dietary interventions have been observed to be more effective than interventions focusing on physical activity *or* dietary behaviors independently (Elliot & Hamlin, 2018; Kohl III & Murray, 2012a), development of smartwatch-based health behavior change interventions should seek to include a balanced physical activity and nutrition health education approach—particularly as many smartwatches allow individuals to track daily energy expenditure and subsequently modify kcaloric intake. If these limitations are addressed, increased effectiveness of smartwatch-based health education interventions might be observed.

Empirical Evidence on Smartwatch Validity/Reliability

Use of smartwatches within health behavior change interventions should also consider the validity and reliability of these devices—particularly as it pertains to

generalizing how health professionals might be able to use these devices' data to promote client/patient health through construction of wellness programs. Two recent reviews have been conducted on the validity and reliability of smartwatch health metric data. In one review, Evenson et al. (2015) examined the validity and reliability evidence for various models of the Fitbit and Jawbone given these two devices' popularity. Observations revealed the two devices to have strong validity for step tracking in laboratory-based settings (all r : > 0.80), but moderate to strong validity when tracking physical activity duration during free-living conditions (r range: $0.36 - 0.86$). Notably, this review also indicated Fitbit and Jawbone devices to generally underestimate energy expenditure. Further, while no reliability studies were found for the Jawbone, interdevice reliability was observed to be high-moderate to strong for the Fitbit when assessing steps, distance, and energy expenditure (r range: $0.71 - 1.0$). More recently, a review by Bunn et al. (2018) evaluated a wider range of smartwatch devices—from companies like Fitbit, Garmin, Apple, Misfit, Samsung, TomTom, and Lumo—based upon validation research conducted between 2015 and 2017 (i.e., research completed after Evenson and colleagues' 2015 review). These researchers came to similar conclusions, observing mostly moderate to strong validity for energy expenditure (r range: $0.16 - 0.99$; 5 of 8 r values above 0.80), heart rate (r range: $0.75 - 0.99$), and step counts (mean absolute percent error: $1.1\% - 22.2\%$), with these health metrics, again, generally underestimated by smartwatch devices. Notably, these researchers stated that difficulty was had in comparing different studies' observations given the inter-study variation of the validation techniques employed. Resultant from the preceding observation, these researchers

suggested standardized criteria need to be developed for future validation studies on these devices to better inform health professionals and consumers alike.

Recent empirical research assessing the validity of multiple different smartwatches (Fitbit One, Misfit Shine, Fitbit Zip, Nike Fuel Band, Withings Pulse, and Jawbone UP) against the research-grade ActiGraph GT3X+ observed strong validity for smartwatch technology in the assessment of steps (all r : > 0.80) and high-moderate to strong validity for energy expenditure (r range: 0.74 - 0.81), but a wider range of validity when evaluating moderate-to-vigorous physical activity duration (r range: 0.52 - 0.91) (Ferguson, Rowlands, Olds, & Maher, 2015). In another study, Diaz et al. (2015) observed high-moderate to strong validity for the step tracking for the wrist-worn Fitbit Flex within a laboratory-based setting versus manually-counted steps (r range: 0.77 – 0.85)—observations somewhat congruent with another more recent investigation of 10 popular smartwatches (Apple Watch Sport, Pebble Smartwatch, Polar Loop, Garmin Vivosmart, Samsung Gear S, Misfit Flash, Jawbone Up Move, Flyfit, Moves, and Fitbit Charge HR) during which these devices demonstrated only moderate validity (mean r : 0.46) during walking sessions at 6.4 kilometers per hour (Fokkema, Kooiman, Krijnen, Van Der Schans, & De Groot, 2017). Fokkema et al. also indicated that when fewer steps were completed during a given trial (i.e., during the slower walking speed sessions), smartwatch validity decreased for step counts.

Smartwatch reliability studies are few. While the aforementioned study by Diaz and colleagues did examine interdevice reliability—observing strong reliability (r : 0.99)—only one study is known to have investigated smartwatch test-retest reliability.

Specifically, Fokkema et al. (2017) (also mentioned previously) observed large variations in test-retest reliability (r range: -0.02 – 0.97) for ten different smartwatches' (referenced above) step measurements during multiple trials of treadmill walking. Although smartwatch validation studies are limited in number, clear is the fact more smartwatch validation studies which include reliability statistics must be conducted. The implications of the limited research on this topic is discussed below.

Importance/Implications of Satisfactory Smartwatch Validity/Reliability

The importance of valid and reliable smartwatch data cannot be understated as it pertains the real-world implications use of this technology might have within the healthcare field. Healthcare paradigms are currently shifting from being reactive (i.e., treating diseases/conditions following onset) to proactive/preventive (i.e., treating diseases/conditions prior to onset). Aligned with this healthcare paradigm shift has been the concept of 'systems medicine' (Hood, Balling, & Auffray, 2012), which employs a multi-faceted treatment approach to wellness by considering an individual's health at the micro-level (e.g., genetic predisposition for certain disease(s)/condition(s)), the meso-level (e.g., interaction between different bodily systems, an individual's health behaviors), and the macro-level (e.g., the environment within which the individual lives). Using big data analysis—briefly defined as the use of advanced statistical techniques/technology to analyze large volumes of varied and complex data (TechAmerica Foundation's Federal Big Data Commission, 2012, p. 10)—researchers/health professionals can utilize modern technologies like smartwatches, social media, etc. to assist with determining how relationships between ourselves and our

built and social environments impact health (Kvedar, 2015).

It has been posited that the use of technologies like smartwatches might allow for implementation of a 'P4 Medicine' structure within the systems medicine framework (Flores, Glusman, Brogaard, Price, & Hood, 2013). To illustrate, the use of a smartwatch to track an individual's various health metrics would facilitate creating a healthcare structure which is: (a) Predictive – information on an individual's health behaviors/patterns could be tracked and correlated with other health indices (e.g., blood pressure, blood lipid levels, blood sugar)—allowing for initial prediction of how an individual's health behaviors might be placing them at risk for certain disease(s)/condition(s) (Selya & Anshutz, 2018); (b) Preventive – knowledge of an individual's poorer health behaviors would assist in the development of health behavior change programs; (c) Personalized – given the provision of individual-level health behavior data, health behavior change programs could be personalized to the lifestyle preferences/limitations of the individual—potentially assisting with increased program adherence and effectiveness (Matthews, Hagstromer, Poher, & Bowles, 2012); and (d) Participatory – use of smartwatch technology and other technology-based platforms (e.g., an online health education platform implemented via social media) could assist individuals in taking a more active approach to improving their health while also educating these individuals on the connection between the small changes they are making to personal health behaviors and improved long-term health outcomes.

If health professionals are to use smartwatch technology in the preceding manner, however, it will be important to ensure that the health metric data being provided is

accurate over time (i.e., valid and reliable) as inaccurate information could hinder the effectiveness of programs developed based upon these data. For example, if a given smartwatch consistently overestimates physical activity duration, a physical activity-based weight loss program developed using these data may fail to produce the desired outcome—namely, weight loss—given the fact the individual using the smartwatch would be observing an inflated physical activity duration value and perhaps not actually meeting their physical activity goals. When considering that smartwatch algorithms consider the duration of physical activity performed when calculating energy expenditure data—a metric which may have some effect on an individual’s self-regulation of caloric consumption—one can see how inaccurate data can derail even the most well-constructed health program. More broadly, consumers purchasing a smartwatch are expecting these devices to measure personal health metrics accurately, with the trustworthiness of smartwatch data recently found to be key in consumers’ intention to use smartwatch devices (Rupp, Michaels, McConnell, & Smither, 2018). Thus, from a business standpoint, smartwatch validation is also key to many technology companies’ “bottom lines”.

As a final note, at the population level, researchers have suggested that novel technologies like smartwatches may assist in promoting health among populations which have less access to health-promoting facilities/structures (e.g., recreation centers/parks, health clinics, supermarkets) such as those living in more rural areas and those of lower socioeconomic status in addition to older adults (An & Shi, 2015; Lobelo et al., 2016). Indeed, metrics such as total daily activity time and steps per day are easily

comprehended by most individuals regardless of their place of residence, socioeconomic status, or age. Therefore, validating smartwatches like the Polar M400 within a free-living setting is important and timely.

Use of Theory in Physical Activity and Nutritional Interventions

Importance of Theory in Health Behavior Change Interventions

Literature is available regarding the importance of theory in the development, implementation, and/or analysis of health behavior change interventions (Brug et al., 2005; Patten, 2014; Thomas, Nelson, & Silverman, 2011a). Collectively, this literature indicates theory to be important for at least three reasons within the context of health behavior change. First, theory facilitates researchers' understanding of the determinants related to individuals' health behaviors and aids in predicting how health behaviors might change from appropriate manipulation of these determinants. Second, resulting from the preceding understanding of determinant-health behavior interactions, theory allows researchers to design and implement more effective health behavior change interventions which target determinants in a systematic manner. Finally, following a health behavior change intervention, use of theory provides researchers the ability to more easily examine and organize the relationships among different variables and explain the phenomena observed. That said, theories vary in relation to: (a) the determinants targeted for change/assessment; and (b) the level at which these determinants are manipulated/evaluated (i.e., the individual-level, environmental-level, or both). Therefore, while inclusion of theory may increase the effectiveness of a health behavior change intervention, choice of theory needs to be weighed against the population and

determinants a researcher desires to impact.

Overview of Health Behavior Change Theories

According to King, Stokols, Talen, Brassington, and Killingsworth (2002), at least three classifications of behavior change theory are available: (a) macro-environmental behavioral theory; (b) micro-environmental behavioral theory; and (c) personal-level behavioral theory. The former two classifications of macro- and micro-environmental behavioral theory are most often seen within health behavior change interventions using the Social-Ecological Model (Bronfenbrenner, 1994) and the Social Cognitive Theory (Bandura, 1977), respectively. Both theories posit interactions between the individual and the environment influence behavior. Notably, the Social Ecological Model considers both the proximal and distal environment (e.g., interpersonal-, organizational-, societal-, and community-level factors) as determining behavior of an individual while the Social Cognitive Theory considers only the more proximal environment (e.g., mainly interpersonal factors like social support) as influencing an individual's behavior.

Given that participation in health behaviors (e.g., physical activity, nutritious eating) involve a complex set of interactions among determinants at the individual- and environmental-levels, the Social Ecological Model, with its macro-environmental approach, has gained increasing popularity among researchers implementing health behavior change interventions (McLaren & Hawe, 2005; USDHHS, 2010). However, limitations have been noted. One major limitation is the Social Ecological Model's limited ability to explain interactions between factors at different environmental levels which influence individual-level health behavior—making intervention development

difficult (Stokols, 1996). As such, researchers have often opted to use micro-environmental approaches, such as the Social Cognitive Theory, to intervene and change health behavior.

Social Cognitive Theory

The ability of the Social Cognitive Theory to aid in targeting and explaining individual-level factors (e.g., self-efficacy, enjoyment, outcome expectancy, barriers) and micro-environmental-level factors (e.g., social support from family/friends and other significant figures) related to behavior change has positioned this theory as a popular and effective choice when implementing health behavior change interventions (Lubans, Foster, & Biddle, 2008; Wallace, Buckworth, Kirby, & Sherman, 2000). This theory posits the concept of reciprocal determinism between the following three factors: (a) Individual characteristics – an individual’s self-efficacy, enjoyment, outcome expectancy, and perceived barriers for a behavior; (b) Environmental factors – an individual’s social environment and the perceived support received for a behavior from family, friends, and other significant figures; and (c) Behavior – pertains to the behavior in question, the skillset and/or knowledge necessary to engage in said behavior, and how the requirements of this behavior might influence individual characteristics and environmental factors and vice versa (Bandura, 2004). For example, if an individual possesses poor physical activity-related self-efficacy/outcome expectancy and is within an unsupportive social environment for physical activity, this individual is less likely to participate in physical activity behavior, with an analogous example able to be made for engagement in nutritious eating behaviors.

Research using the Social Cognitive Theory in health behavior change interventions has observed improvements in environmental factors and individual characteristics which have led to subsequent behavior changes. Regarding environmental factors, research has highlighted the pivotal role of social support. Among youth, parental and/or peer social support has been observed to increase physical activity participation (Dowda, Dishman, Pfeiffer, & Pate, 2007; Hohepa, Scragg, Schofield, Kolt, & Schaaf, 2007) while peer support has been found most important in promoting young adults' and adults' physical activity participation (Cavallo et al., 2012; Edney et al., 2017; Maher et al., 2015; Voorhees & Young, 2003). Further, in a study by Marr and Wilcox (2015), social support was observed important in the relationship between college students' locus of control and physical activity/nutritious eating behaviors.

Individual characteristics are also important in the promotion of proper physical activity and dietary behaviors. For example, research has indicated improved self-efficacy to promote increased physical activity in adolescent girls (Dishman et al., 2004), with improvements in self-efficacy also promoting individuals' outcome expectancy regarding physical activity (i.e., promoting more positive than negative attitudes toward physical activity) among youth (Gao, Lee, Solmon, & Zhang, 2009) and young adults (Rovniak, Anderson, Winett, & Stephens, 2002). Studies among college students have observed self-efficacy to predict college students' positive physical activity and nutritious eating behaviors (Marr & Wilcox, 2015; Mirzaei-Alavijeh et al., 2018; Von Ah, Ebert, Ngamvitroj, Park, & Kang, 2004), with self-efficacy and outcome expectancy observed in another study to explain 29% of the variance in college students' physical activity

behaviors (Sriramatr, Silalertdetkul, & Wachirathanin, 2016). These observations are congruent with earlier studies on the association of Social Cognitive Theory-related determinants of physical activity and other health behaviors among college students (Doerksen, Umstattd, & McAuley, 2009; Farren, Zhang, Martin, & Thomas, 2017; Petosa, Suminski, & Hertz, 2003; Rovniak et al., 2002) which have most often observed self-efficacy, social support, and outcome expectancy to be the greatest predictors of college students' health behaviors. Finally, studies have indicated that college students who perceive greater barriers to health behavior engagement are less likely to participate in proper health behaviors (Blake, Stanulewicz, & McGill, 2017; Grubbs & Carter, 2002). As for technology-based health behavior change interventions among college students, Cavallo et al. (2012) found a 10-week Social Cognitive Theory-based intervention using social media to be effective at promoting increased physical activity-related energy expenditure of approximately 500 kcalories per day among this population.

Undoubtedly, the utility of the Social Cognitive Theory in the development and implementation of health behavior change interventions has meant great popularity among researchers, with the research reviewed highlighting this theory's efficacy in the promotion of health behavior change when implemented within physical activity and dietary interventions. Researchers employing the Social Cognitive Theory are seeking to promote individuals' motivation for engaging in health behaviors through the improvement of individual characteristics, environmental factors, and behavioral factors. Yet, for health behavior changes to be maintained by individuals long-term, intrinsic

motivation is also an important psychosocial construct to consider and a construct that the Social Cognitive Theory does not include. Investigation of intrinsic motivation requires consideration of the Self-Determination Theory (Ryan & Deci, 2000)—a personal-level behavioral theory.

Self-Determination Theory

According to Ryan and Deci (2000), individuals seek novel challenges to fulfill three basic psychological needs: (a) Self-determination/autonomy – individuals desire to be self-dependent and obtain an internal locus of control for a behavior/activity; (b) Competence – individuals seek mastery of a behavior/activity; and (c) Relatedness/social interactions – individuals desire development and participation in social interaction while engaged in a certain behavior/activity. As greater degrees of the preceding needs are met by an individual, motivation for engaging in a certain behavior/activity increases. Ryan and Deci (2000) further postulated that this motivation will increase along a continuum, with three separate categories of motivation outlined. Of note, these authors also stated that within each motivation category lies one or more types of self-regulation for a behavior. Below is an overview of the three motivation categories and each motivation category's self-regulation type(s):

(a) *Amotivation* – Lack of motivation for engaging in a behavior.

(i) *Non-Regulation* – An individual is not motivated by and/or does not value the behavior/activity and, thus, does not put forth any effort to engage in said behavior/activity. This outcome might result, for example, from an

individual not feeling competent enough to participate in the behavior/activity (Bandura, 1986).

(b) *Extrinsic Motivation* – Motivation is present for engaging in a behavior, but this motivation exists across a continuum of varying degrees of external- and internal-regulation.

(i) *External-Regulation* – Individuals engaging in this type of regulation often do so in order to meet external demands, receive a reward, or to avoid punishment (Lox, Martin-Ginis, & Petruzzello, 2014).

(ii) *Introjected-Regulation* – Slightly more self-controlled than external-regulation. Individuals engaging in introjected-regulation most often participate in a behavior/activity to circumvent guilt or anxiety regarding not participating or to receive ego-building praise from others (Deci & Ryan, 1995).

(iii) *Identified-Regulation* – Individuals engaging in identified regulation are doing so as the behavior/activity is beginning to become personally important and has achieved a certain degree of value in their life.

(iv) *Integrated-Regulation* – Upon assimilating a behavior/activity within the self, integrated-regulation has been achieved. Individuals engaging in integrated-regulation see a behavior/activity closely aligned with personal values (Lox et al., 2014). While many characteristics of integrated-regulation mirror that of intrinsic motivation/regulation (see below),

individuals using integrated-regulation are still engaged to a small degree in a behavior/activity due to some type of external motivation.

(c) *Intrinsic Motivation* – The most self-determined state of motivation.

(i) *Intrinsic-Regulation* – An individual engaging in intrinsic-regulation is participating in a behavior/activity not only because the action aligns with their values, but because of the inherent satisfaction participation in the behavior/activity brings. Theoretically, this individual would need no external motivation to continue participation in the behavior/activity.

Researchers and health professionals using the Self-Determination Theory desire to help individuals move from amotivation and externally-regulated forms of extrinsic motivation to greater levels of internally-regulated forms of extrinsic motivation and, ultimately, intrinsic motivation. Literature indicates that interventions which promote more internally-regulated forms of regulation (i.e., identified-, integrated-, and intrinsic-regulation) by increasing physical activity- and nutrition-related competence can promote increased physical activity and weight loss among adults (Silva et al., 2010), with literature among college students also indicating that more internally-regulated forms of regulation are more predictive of exercise behavior (Farmanbar, Niknami, Lubans, & Hidarnia, 2013). Other literature has also found college students' initiating exercise and wellness programs to have greater behavioral intentions to adhere to these programs if greater intrinsic rewards (e.g., stress reduction, enjoyment) for these programs are perceived (Phillips, Chamberland, Hekler, Abrams, & Eisenberg, 2016). Conversely, high levels of amotivation and decreased self-determined motivation can lead to boredom and

discontinuation of activity among participants engaged in a physical activity (Gao, 2012) and other health interventions (Farmanbar et al., 2013). Thus, interventions utilizing the Self-Determination Theory should focus attention on increasing competence for health behaviors which might then result in improved autonomy for participating in health behaviors such as physical activity and nutritious eating.

Among the limitations of previous smartwatch-based health behavior change interventions was the lack of a health education component despite the importance of health literacy in long-term health behavior participation (Nielsen-Bohlman et al., 2004; Rikard et al., 2016). One proposed medium by which to deliver health education to a larger and more diverse group of individuals is social media due to this technology's broad reach and heavy societal integration (Welch et al., 2018). Thus, given the fact the Social Cognitive Theory targets personal- (i.e., self-efficacy, enjoyment, outcome expectancy, barriers) and micro-environmental (i.e., social support) factors which can synergistically affect an individual's likelihood of participation in a behavior, a combined smartwatch-based and Social Cognitive Theory-related, social media-delivered health education intervention may be effective at promoting health behavior change as this type of intervention would target improving factors at both the personal- and micro-environmental levels. Further, structuring health education to also promote increased Self-Determination Theory-related self-determination/autonomy, competence, and relatedness is prudent. Specifically, given intrinsic motivation's positive relationship with long-term health behavior participation (Farmanbar et al., 2013; Phillips et al., 2016), the promotion and evaluation of the constructs which facilitate improved intrinsic motivation

within the preceding type of intervention design is warranted. Therefore, a combined smartwatch-based and Social Cognitive Theory- and Self-Determination Theory-related, social media-delivered health education intervention to promote greater physical activity and nutritious eating behaviors is needed. College students, a cohort alluded to during the discussion of these two theories, may be the ideal population for an intervention of this type.

Health Concerns and Health Wearable/Social Media Use in Young Adult College Students

Across all race/ethnicities, the obesity prevalence among individuals 20-39 years of age is 32.3% (Ogden et al., 2015). Unfortunately, physical inactivity and poor dietary practices among this age cohort appear to be two major contributory factors for the preceding statistic, with the youngest individuals within this cohort being college students. Research has suggested college students possess risk factors for overweight and obesity as many of these individuals are now independent and, for some, making physical activity- and nutrition-related decisions autonomously for the first time (Deliens et al., 2015; Desai et al., 2008; Wengreen & Moncur, 2009). Studies on obesity- and weight-related behaviors in this population suggest approximately 25% to 30% of college students are overweight or obese (Nelson et al., 2007; Peterson et al., 2018; Sira & Pawlak, 2010) and can engage in upwards of 10 to 11 hours of sedentary behavior daily, with concurrently low daily physical activity (Peterson et al., 2018; Smetaniuk et al., 2017).

Poor nutritional behaviors also contribute to overweight/obesity risk factors among

this population. In a study among college freshman and sophomores, Racette et al. (2005) found that 70% of the 764 college students assessed consumed less than the USDA recommendations of two cups of fruit and three cups of vegetables daily (USDA, 2015). Strikingly, approximately half of the students surveyed also reported high-fat fast or fried food consumption $\geq$ three times in the past week. Notably, a subsample of these students was assessed again a year later with 70% of these students gaining, on average, four kilograms (Racette et al., 2005). Other studies have demonstrated that in addition to not eating the recommended amounts of fruit and vegetables, college students were also not meeting daily whole grain intake recommendations and were frequently consuming sugar-sweetened beverages (Larson et al., 2010; Levitsky, Halbmaier, & Mrdjenovic, 2004). These dietary practices (e.g., high consumption of sugar-sweetened beverages, low consumption of fruits, vegetables, and whole grains) are likely a product of obesogenic environments surrounding college students (e.g., continuously eating at buffet-style student dining halls)—factors that, when combined, can promote positive long-term energy balance and weight gain over the college years (Giskes et al., 2011; Levitsky et al., 2004). Weight gain among college students is concerning as upward weight trajectories in young adulthood have been observed predictive of higher body mass index in middle age (Malhotra, Ostbye, Riley, & Finkelstein, 2013).

Given the preceding information, not only is it clear that theoretically-backed physical activity interventions are needed among college students, there is also a distinct need to include a dietary component within these interventions. Technology integration within these physical activity and dietary interventions among college students might

present a viable approach (Partridge & Redfern, 2018), with college students stating that the use of physical activity and dietary intervention strategies congruent with their lifestyles as an important factor in their willingness to participate (Martinez, Harmon, Nigg, Bantum, & Strayhorn, 2016). When examining the paucity of randomized smartwatch-based health behavior change interventions among college students, however, largely null observations have been made.

An empirical study investigating the use of the Jawbone UP to improve African American female college students' physical activity did not observe provision of this device to promote increased daily steps over the six-week trial versus a similar physical activity-related smartphone application and, further, noted significantly decreased daily steps versus the group utilizing the physical activity-related smartphone application at the eight-week follow-up (Melton et al., 2016). Another study by Kim et al. (2018) among college students provided a Misfit Flash smartwatch and enrolled in a health-related college course observed no change in moderate-to-vigorous physical activity and increased sedentary behavior over the course of a 15-week intervention. These observations were not different from those participants within the comparison group only enrolled in the health-related course. Finally, potentially positive observations were made in a study by Rote (2017), who found significantly increased steps per day (~ 1,000 steps) over 16 weeks among college students using a Fitbit to track physical activity and concurrently enrolled in an introductory health course when compared to a group enrolled exclusively in the health course and a control group. Yet, these observations were brought into question as significantly increased steps/day were only observed using the

study-related pedometer, with the experimental group's Fitbit data indicating a significant decline in steps per day from pre- to post-intervention of approximately 2,500 steps.

It is important to note, however, these studies made little to no mention of the use of an established health behavior change theory in the trials' development and implementation, with no trial having evaluated changes in any physiological (e.g., weight, body fat percentage, cardiorespiratory fitness), psychosocial (e.g., self-efficacy, enjoyment, outcome expectancy, barriers, social support, intrinsic motivation), or dietary (e.g., sugar-sweetened beverage consumption; intake of fruits, vegetables, and whole grains) outcomes. While physical activity participation is important, the investigation of other health correlates/outcomes is also necessary given how significant psychological well-being and physiological characteristics like body weight and body fat percentage are when evaluating overall health (National Wellness Institute, 2018). Further, while Kim and colleagues (2018) did include intervention fidelity protocol, this investigation was the single study to do so, with this fidelity protocol only implemented once during the 15-week intervention suggesting that more frequent intervention fidelity measures may be needed to ensure adequate intervention adherence and effectiveness. Finally, while a health education component was also included in the studies by Kim and colleagues (2018) and Rote (2017), these educational components largely focused on physical activity, with nutrition a lesser concern. This is notable as empirical evidence has suggested that incorporating components of physical activity and nutrition health education in health behavior change interventions is more effective for improving health outcomes than focusing on either component exclusively (Elliot & Hamlin, 2018; Kohl

III & Murray, 2012a). Additionally, both studies' health education component was provided via college health course attendance which may have presented some participant burden and limits the generalizability of these findings to only those attending college.

These studies indicate future investigations of the effectiveness of smartwatch use within health behavior change interventions should make the following improvements: (a) use an established health behavior change theory in the development and implementation of the intervention; (b) evaluate a more diverse array of outcomes including physiological, psychosocial, and dietary outcomes; (c) implement intervention fidelity protocol more frequently (e.g., every two to three weeks) throughout the intervention's duration; and (d) include a balanced physical activity- and nutrition-related health education component as part of the intervention.

Research has also indicated the popularity of social media among young adults. Indeed, research has indicated that seven-in-10 U.S. adults possess a social media account, with approximately 90% of individuals 18-29 years of age using at least one social media site (Perrin, 2015). Currently, Facebook represents the most widely used social media site with 1.71 billion active users (Statista, 2016c) and individuals 18 to 34 years of age representing the majority of Facebook users (Statista, 2016b). Randomized-controlled trials on the use of social media-based to promote health behavior change have observed this technology to be effective at improving physical activity participation among college students (Cavallo et al., 2012) and adults (Maher et al., 2015), with further research stating the use of social media sites like Facebook may be an attractive platform

upon which to deliver health education to intervention participants (Edney et al., 2017; Welch et al., 2018). Again, as college students have stated the need for physical activity and dietary interventions to be congruent with their lifestyles (Martinez et al., 2016), a technology-based health behavior change intervention among college students might consider using a social media platform like Facebook to supplement smartwatch use and deliver physical activity- and nutrition-related health education to this population in a manner well-integrated into this population's lifestyle.

Therefore, the combined use of wearable technology and a theoretically-grounded, social media-delivered health education intervention may prove appealing and effective as a health behavior change strategy among college students. Specifically, use of the Polar M400 may increase college students' ability to self-regulate physical activity behaviors as self-regulation is posited as an important factor in promoting behavior change (Bandura, 1991). Further, the Polar M400's functionality also allows for users to view energy expenditure as well, which may allow individuals to self-regulate kcaloric intake in relation to daily energy expenditure. In combination with the Polar M400's capabilities, a twice-weekly Social Cognitive Theory- and Self-Determination Theory-based, Facebook-delivered health education intervention may be able to increase college students' self-efficacy, enjoyment, outcome expectancy, social support, and intrinsic motivation while decreasing barriers for participation in greater physical activity and nutritious eating behaviors.

Summary

The paucity of current high-quality randomized studies conducted to date regarding smartwatch use in the promotion of increased physical activity have made mixed observations. Limitations exist, however, within the preceding literature. Specifically, most, if not all, studies lacked: (a) a sound theoretical backing—despite the importance of theory in the promotion of behavior change (Brug et al., 2005; Patten, 2014; Thomas et al., 2011a); (b) a standardized intervention fidelity protocol to ensure participant adherence to intervention protocol and potentially increased intervention effectiveness (Borrelli, 2011); (c) a health education component—as has become a major emphasis among participatory research (Nielsen-Bohlman et al., 2004; Rikard et al., 2016); and (d) an emphasis on nutrition—an addition which research has suggested might increase the effectiveness of health behavior change interventions on improving health outcomes when compared to concentrating exclusively on promoting physical activity or nutritious eating exclusively (Kohl III & Murray, 2012a; Welch et al., 2018). As college students have been observed to be physically inactive (Desai et al., 2008; Peterson et al., 2018) and to engage in poorer dietary behaviors (Giskes et al., 2011; Larson et al., 2010; Racette et al., 2005), but represent a technology-savvy population (Perrin, 2015), a theoretically-grounded, technology-based physical activity and dietary intervention might prove effective among this population. Specifically, it is worth examining whether a health behavior change intervention combining smartwatch use with a theoretically-grounded, social media-based health education intervention might assist college students in greater participation in physical activity and nutritious eating behaviors while also

improving physiological and psychosocial health outcomes. Finally, further investigation of smartwatch validity and reliability will provide information essential to ensuring that the physical activity and dietary interventions/programs which might be developed based upon smartwatch data is not misleading consumers and/or health professionals and decreasing intervention/program effectiveness. If this intervention methodology is observed to be feasible and effective, with the Polar M400's health metric data observed to be valid and reliable, the current study's methodology may be able to be scaled and applied to other populations by health professionals—potentially effecting change in population-level health.

Chapter Three: Methodology

The Consolidated Standards of Reporting Trials (CONSORT) guidelines were used when drafting this dissertation (Schulz, Altman, Moher, & Group, 2010), with each component and its associated location within this document listed in Appendix A. Additionally, the current study is registered at ClinicalTrials.gov (Study #: NCT03253406).

Participants

Thirty-eight college students from the University of Minnesota-Twin Cities campus participated in this 12-week randomized pilot study focused on improving physical activity and nutritious eating behaviors. Recruitment took place via flyer/email communication and in-person recruitment presentations. Inclusion criteria were: (a) 18-35 years old; (b) body mass index ≥ 18.5 ; (c) having not engaged in physical activity levels above the Physical Activity Guidelines for Americans over the last month (PAGAC, 2018; USDHHS, 2008)—verified through a structured and scripted screening interview prior to each participant’s baseline testing and randomization (see Appendix E); (d) currently eating less than the recommended two cups of fruit and three cups of vegetables per day (USDA, 2015)—verified prior to baseline testing and randomization using a 10-item fruit and vegetable food frequency questionnaire (see Appendix F; Thompson, Subar, Smith, et al., 2002); (e) no self-reported diagnosed physical/mental disability; (f) provided informed consent (see Appendix C) and completed the Physical Activity Readiness Questionnaire (see Appendix D); and (g) was willing to be

randomized into an experimental or comparison group. Conversely, exclusion criteria were: (a) self-reported diagnosed physical/mental disability; and (b) contraindication(s) to physical activity participation as determined by responses on the Physical Activity Readiness Questionnaire. University IRB approval was obtained prior to any recruitment/data collection (see Appendix B), with all procedures performed with the participants in accordance with the ethical standards of the Institution and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards (World Medical Association, 2018).

A power analysis for a balanced one-way ANOVA stated the need for 45 individuals in each group to detect a difference of 4 minutes in moderate-to-vigorous physical activity between the experimental and comparison groups (parameters for power analysis: $k = 2$ groups, $f = 0.3$, significance level = 0.05, and power = 0.8). This effect size was calculated based upon the difference between experimental and comparison group post-intervention means for daily minutes of moderate-to-vigorous physical activity among college student participants in the researcher's previous technology-based health intervention. This difference was then divided by the pooled standard deviation for mean daily minutes of moderate-to-vigorous physical activity (i.e., $[[\text{mean for intervention group}] - [\text{mean for comparison group}]/\text{pooled standard deviation}]]$) as demonstrated by Coe (2002). Given the limited amount of time during which to recruit college students each of the two semesters the study was conducted (~ three weeks) and the stringent inclusion criteria, the above recruitment goal was unattainable despite high study interest (see results section).

Randomization

A 12-week two-arm randomized pilot trial design was used: (a) Experimental Group-Polar M400 + Facebook Group – Group was provided a Polar M400 smartwatch to track physical activity duration, steps per day, and energy expenditure while also being included in a Facebook group wherein Social Cognitive Theory- and Self-Determination Theory-based physical activity and nutritious eating health education tips (see Appendix L for tips) were provided twice weekly for 12 weeks (see Appendix M for experimental group’s Facebook page); and (b) Comparison Group-Facebook Only Group – Group was included exclusively in a separate, but content-identical, Facebook group for 12 weeks (see Appendix N). No interaction among group peers/researchers was explicitly encouraged. Notably, the researcher chose to include comparison participants only within a theoretically-grounded, Facebook-delivered health education intervention *instead of* providing these participants with only a smartwatch given the fact previous social media-based health behavior change interventions have demonstrated some positive effects (Cavallo et al., 2012; Maher et al., 2015). As seen in the literature review above, the same cannot be stated for most smartwatch-based health behavior change interventions. Thus, the researcher considered it important to compare the proposed novel methodology to a methodology which has had some success at promoting health behavior change. Finally, as a true control group might have been perceived unethical and a delayed-intervention control rendered difficult given the researcher’s impending graduation, the current study design was considered adequate to address/evaluate the stated research aims/hypotheses.

All qualified participants completed in-Lab testing assessing demographic,

physiological, and psychosocial outcomes at baseline and 12 weeks. Further, at baseline, six weeks, and 12 weeks, ActiGraph Link accelerometers were distributed to all participants for a seven-day period to evaluate habitual physical activity behaviors (i.e., sedentary behavior, light physical activity, and moderate-to-vigorous physical activity as well as steps per day) in addition to each participant being sent an email request to fill out the National Cancer Institute's Automated Self-Administered 24-Hour (ASA24) Food Recall on three non-consecutive random days (two weekdays and one weekend day) during that same seven-day period to assess habitual dietary behaviors. Notably, upon returning the ActiGraph Link after the baseline seven-day testing period, participants were informed of the group into which they were randomized (determined using a random numbers table and a 1:1 group allocation ratio). Participants randomized into the experimental group met with the researcher to discuss the Polar M400's functions, with participants in both groups instructed on how to access and use their respective Facebook groups. Specifics regarding all testing can be found in the "Procedures" subsection below.

Data Collection Instruments

Primary Outcome

Physical Activity. Assessed via ActiGraph Link accelerometers, with daily moderate-to-vigorous physical activity, light physical activity, sedentary behavior, and steps per day the outcomes of interest. Previously, hip-mounted versions of the ActiGraph accelerometer have been validated among adults (Kaminsky & Ozemek, 2012). Given the recent introduction of the ActiGraph Link, however, no previously

validated cut points exist, with only a paucity of literature available having used this device to conduct physical activity assessments thus far. Specifically, of the 11 total studies found using the ActiGraph Link, only two used this device to assess physical activity in free-living and/or simulated free-living settings (Bedard et al., 2017; Montoye et al., 2017)—settings most applicable to the current study. Fortunately, both investigations were conducted among college students, with the study most analogous to the present investigation being that of Bedard et al. (2017). Thus, the present study's researcher contacted both studies' first and corresponding authors to acquire the cut points used in those investigations for application to the current study's data analysis. These researchers stated that since no validated cut points have yet to be developed for the ActiGraph Link, the best analysis method for use with the ActiGraph Link would be minute-by-minute stepping rate—a methodology previously employed in other studies of free-living physical activity to determine sedentary behavior, light physical activity, and moderate-to-vigorous physical activity durations in addition to steps per day (Ayabe, Junichiro, Kumahara, & Tanaka, 2011; Tudor-Locke et al., 2011).

Congruent with the preceding studies' minute-by-minute stepping rate methodology, the following cut points—in steps per minute—were used: sedentary behavior: 0 – 19; light physical activity: 20 – 99; moderate-to-vigorous physical activity: ≥ 100 . A 60-second epoch was used to facilitate the assessment of minute-by-minute stepping rate. Participants wore the accelerometer for seven days (ensuring the collection of physical activity data on at least two weekdays and one weekend day) as suggested for field-based accelerometer research (Troost, McIver, & Pate, 2005), with participants in the

experimental group wearing the accelerometer on the same wrist as the Polar M400 to facilitate later validation analyses. Accelerometry measurements were taken at baseline, six weeks, and 12 weeks to examine changes over time in the aforementioned outcomes, with participants' physical activity data only considered valid if at least 12 hours per day of wear time was observed on two weekdays and one weekend day using ActiLife software (v. 6.13.3; Pensacola, FL) (Herrmann, Barreira, Kang, & Ainsworth, 2013; Trost et al., 2005). These data were then exported to and analyzed within Microsoft Excel (Microsoft Inc.; Redmond, WA) where "COUNTIFS" and "AVERAGE" functions were employed to determine mean sedentary behavior, light physical activity, and moderate-to-vigorous physical activity durations in addition to steps per day.

It should be noted that despite the lack of validated cut points for the ActiGraph Link, this accelerometer was chosen given the researcher's desire to validate the Polar M400 smartwatch's health metric data. Validation of the Polar M400's data necessitated the use of a research-grade accelerometer capable of also being worn at the wrist (i.e., the same location as the Polar M400 smartwatch). Further, it is worthwhile to highlight that the ActiGraph Link was provided to all participants for seven-day periods at baseline, six weeks, and 12 weeks. Only data from the ActiGraph Link were used to discern changes in physical activity and sedentary behavior over time within and between groups. Validation analyses were facilitated simply by asking the experimental group participants to simultaneously wear both the ActiGraph Link and Polar M400 on the same wrist at the six and 12 week time points (see "Procedures" subsection).

Secondary Outcomes

Cardiorespiratory Fitness. Evaluated with the YMCA 3-Minute Step Test (Golding, Meyers, & Sinning, 1998). Participants stepped up and down for three minutes on a 12-inch riser to a metronome set at 96 beats per minute (each beep corresponding to one movement of the leg, with 4 beeps representing one “up-down” cycle). Participants’ heart rate was assessed immediately for one minute following the conclusion of the test via palpation of the radial artery by the researcher. Heart rates were then compared to age- and sex-based normative values published by the YMCA (Golding et al., 1998), with participants stratified into the following cardiorespiratory fitness categories: (a) excellent; (b) good; (c) above average; (d) average; (e) below average; (f) poor; and (g) very poor. The normative heart rate values for both sexes for the age groups included within the current study are included in Table 3-1. The step test was performed at baseline and 12 weeks to assess changes in cardiorespiratory fitness over time as evidenced by (a) mean difference in post-step test heart rate from baseline to 12 weeks; and (b) each participant’s normative cardiorespiratory fitness category movement from baseline to 12 weeks.

Table 3-1. Normative Cardiorespiratory Fitness Categories by Age and Sex

	18-25 years old		26-35 years old	
	Male	Female	Male	Female
Excellent	50-76	52-83	51-78	58-83
Good	77-86	84-94	79-86	84-93
Above Average	87-93	95-103	87-95	94-102

Average	94-101	104-112	96-103	103-112
Below Average	102-109	113-120	104-112	113-121
Poor	110-121	121-133	113-124	122-132
Very Poor	122-157	134-169	125-161	133-171

Note. All heart rate values are in beats per minute.

Height, Weight, and Body Composition. Height was measured to the nearest half-centimeter using a Seca stadiometer (Seca; Hamburg, Germany), with weight measured using a Tanita BC-558 IRONMAN® Segmental Body Composition Monitor (Tanita; Tokyo, Japan), with participants in lightweight athletic clothing. This scale was also used to conduct body composition measurements via bioelectrical impedance. Bioelectrical impedance sends a small electrical pulsatile wave through the body. Muscle is more conducive to electrical current transmission due to its higher water content versus fat meaning individuals with higher proportions of lean mass (i.e., lower proportions of fat mass) will not impede the current to the degree of individuals with higher fat mass; therefore registering lower body fat percentage values. Bioelectrical impedance has proven a valid field measure of body composition in young adults (Aandstad, Holtberget, Hageberg, Holme, & Anderssen, 2014). Notably, to decrease confounding factors for these body composition measurements, participants were asked to come in for their 12-week testing session at approximately the same time of day and having eaten/drunk similar foods/beverages the night before as they did prior to baseline testing. The preceding measurements were taken at baseline and 12 weeks, with measurements recorded on the participant demographic information sheet (see Appendix G).

Social Cognitive Theory-Related Self-Efficacy. Measured by a six-question measure

developed and validated by Carlson et al. (2012) wherein participants rated how confident they felt in overcoming certain barriers (e.g., “...exercise when I am tired” or “...exercise when I feel I don’t have time”) on a five-point Likert scale (1: *not confident at all* to 5: *extremely confident*). Notably, the sixth item on the scale assessed participants’ confidence to make time for at least 30 minutes/day of physical activity—consistent with national physical activity recommendations (PAGAC, 2018; USDHHS, 2008). This scale has demonstrated good internal consistency for self-efficacy (alpha for men: 0.76; alpha for women: 0.80) and adequate convergent validity (r range: 0.19 – 0.22) for this outcome when correlated with physical activity measurements. Items on this scale were summed (range: five to 30) and averaged in accordance to scoring protocol, with higher scores representing greater self-efficacy. Self-efficacy was assessed at baseline and 12 weeks, with this scale available in Appendix G.

Social Cognitive Theory-Related Social Support. Assessed using a five-question measure also developed and validated by Carlson et al. (2012), with participants rating on a five-point Likert-type scale (1: *almost never* to 5: *almost always*) how often significant others provide health-related support/encouragement. Akin to the self-efficacy scale above, this scale has demonstrated good internal consistency for social support (alpha for men: 0.89; alpha for women: 0.85). Per scoring protocol, this scale’s items were summed, with a range from five to 25, after which an average was taken. Higher values indicated greater social support. This scale is available in Appendix G. Evaluation of social support occurred at baseline and 12 weeks.

Social Cognitive Theory-Related Enjoyment. A five-question measure validated by

Ommundsen, Page, Po-Wen, and Cooper (2008) examined participants' enjoyment.

Briefly, participants rated agreement with statements like "I have more fun engaging in physical activity than doing other things" on a three-point scale (1: *Disagree* to 3: *Agree*). Responses were summed, with a range from five to 15, and then averaged, with higher values indicating greater enjoyment. The internal consistency of this scale has been reported to be adequate (alpha range: 0.51 – 0.62). Of note, response four, "I usually prefer to watch rather than engage in physical activity" was reverse coded during analysis. Baseline and 12 weeks assessments of enjoyment were completed, with this scale found in Appendix G.

Social Cognitive Theory-Related Barriers. Evaluated via a validated 14-question measure, with participants asked to rate agreement between hypothetical barriers and their own perceived barriers on a four-point Likert-type scale (1: *strongly disagree* to 4: *strongly agree*) (Sechrist, Walker, & Pender, 1987). This barriers scale has a reported internal consistency of 0.89 and a test-retest reliability of 0.77. Congruent with scoring protocol, items were summed, with a range of 14 to 56 and greater scores indicating higher perceived barriers for health behaviors. Barriers were examined at baseline and 12 weeks. This scale can be found in Appendix G.

Social Cognitive Theory-Related Outcome Expectancy. Assessed with a modified 12-question measure developed by Gesell et al. (2008) using a dichotomous structure (1: *Yes* and 0: *No*) to determine whether participants agreed with responses originating from the stem "If I was to exercise on most days it would...". Sample responses were "give me more energy" and "help to control my weight". Four responses (i.e., "...it would be

boring”; “...it would result in injury”; “...it would embarrass me in front of others”; and “...it would make me tired”) were reverse coded during analysis. Internal consistency of this scale has been shown to be adequate (alpha range: 0.58 – 0.75). Responses were summed, with higher scores indicative of more positive outcome expectancy. Measurement of outcome expectancy took place at baseline and 12 weeks, with this scale presented in Appendix G.

Self-Determination Theory-Related Intrinsic Motivation. Evaluated using the interest/enjoyment subscale of the Intrinsic Motivation Inventory (McAuley, Duncan, & Tammen, 1987). This seven-question subscale required participants to determine how true certain statements such as “I enjoyed this activity very much” and “I would describe this activity as interesting” were to them on a seven-point Likert-type scale (1: *not at all true* to 7: *very true*). The interest/enjoyment scale of the Intrinsic Motivation Inventory has demonstrated good internal consistency (alpha: 0.78) (Deci, Eghrari, Patrick, & Leone, 1994; McAuley et al., 1987). Pursuant with scoring protocol, responses were summed (range: seven to 49) and averaged, with higher scores indicating greater intrinsic motivation. During analysis, two responses (i.e., “I think physical activity is a boring activity” and “Physical activity does not hold my attention at all”) were reverse coded. Appendix G contains this scale. Intrinsic motivation was evaluated at baseline and 12 weeks.

Nutritious Eating Behaviors. Examined using the National Cancer Institute’s ASA24 Dietary Recall which required participants to recall all foods consumed during the previous day. The ASA24 has been validated in previous research (Kipnis et al.,

2003; Moshfegh et al., 2008). Participants received unique login information allowing them to access and complete each Recall after which the researcher downloaded and analyzed the results. The ASA24 was administered three times on non-consecutive random dates (two week days and one weekend day) during the seven-day baseline, six week, and 12 week testing periods (i.e., nine total recalls), with participants notified in advance that they would be asked to complete this assessment. Literature has stated that multiple days of food recalls are necessary in prospective studies which desire accurate estimations of habitual food/nutrient intake to account for the day-to-day variability which may be present in individual's diets and for comparison to national dietary recommendations (Baranowski, 2013; Willett, 2013).

Concentration was placed on examining changes in participants' daily kcaloric intake, fruit and vegetable consumption, whole grain consumption, and intake of sugar-sweetened beverages. Notably, fruit and vegetable consumption were reported in cups, with vegetable consumption further subdivided into vegetable consumption including and excluding legumes to ensure variations in dietary preferences were accounted for. Additionally, whole grain consumption was reported in ounce equivalents allowing easier comparison of participants' whole grain consumption to national recommendations. Finally, sugar-sweetened beverage consumption was reported in daily cups and kcaloric intake. Congruent with previous literature utilizing the ASA24 (Wang, Bleich, & Gortmaker, 2008) and recommendations regarding sugar-sweetened beverage classifications (Popkin et al., 2006), a sugar-sweetened beverage within the current study included the following non-alcoholic beverages: sports drinks, fruit drinks/punches (those

not 100% juice), soda, low-kcalorie drinks, sweetened tea/coffee, and other sweetened beverages (e.g., flavored milk). To ensure inclusion of all sugar-sweetened beverages, all items each participant consumed at baseline, six weeks, and 12 weeks were reviewed, with all non-beverage items removed. Next, beverages not meeting the preceding criteria were omitted (e.g., non-flavored milk, unsweetened water, alcohol). Finally, the items left were then validated by viewing the “ADD_Sugar” column within the ASA24 output which highlights any added sugar included in the beverage reported. Any item which registered “0” for added sugar was omitted from further analysis.

Adherence to Social Media-Delivered Health Intervention. Regardless of Group allocation, adherence to the social media-delivered health education intervention previously outlined was tracked. In detail, the researcher determined whether the participants had read the Facebook-delivered health education tips using two indicators. First, Facebook’s “Seen By” function automatically indicated and listed everyone who interacted with a new posting within each participant’s respective Facebook group. Second, to back up the results of reviewing the “Seen By” function, the researcher asked participants to “Like” each of the posts they read. Using these two indicators, the researcher kept a running tally for each participant—only assigning a point for participants which Facebook indicated had “Seen” and subsequently “Liked” the post they read. A possible 24 points were available, with percentage adherence calculated by dividing the number of points each participant received by 24.

Use/Acceptability. During the 12-week testing session, participants from both groups were surveyed with additional questions regarding the helpfulness of the

Facebook-delivered health education tips on a 7-point Likert scale (1: *Very Unhelpful* to 7: *Very Helpful*) and their implementation frequency of these tips on a 6-point Likert scale (1: *Never* to 6: *Daily*). Moreover, the experimental group was queried on whether they believed the Polar M400 to have been beneficial in the tracking and modification of physical activity behaviors on a 7-point Likert scale (1: *Not Very Useful* to 7: *Very Useful*) and asked to rate the device's ease-of-use on a 7-point Likert scale (1: *Very Difficult* to 7: *Very Easy*). Finally, using two open-ended questions, experimental participants were then asked what they believed were some positive and negative features of the device. These additional questions are listed within Appendix H.

Procedures

All potential college student participants first came into the University of Minnesota's Physical Activity Epidemiology Laboratory to complete baseline screening. To assess baseline moderate-intensity physical activity levels, the researcher read verbatim a moderate-intensity physical activity screening questionnaire which screened for the type of physical activity the potential participant had participated in during the previous month. Further, this questionnaire surveyed the mean weekly frequency with which the potential participant had engaged in bouts of moderate-intensity physical activity ≥ 10 minutes as well as the mean minutes per bout. By multiplying the mean frequency by mean minutes per bout, the researcher was able to determine whether the potential participant was participating in < 150 minutes of moderate-intensity physical activity per week. Regarding the assessment of baseline fruit and vegetable consumption, the researcher used a 10-item fruit and vegetable food frequency questionnaire developed

by F. Thompson, Subar, Brown, et al. (2002). This food frequency questionnaire contains two and seven questions related to the frequency and amount of fruit and vegetable consumption, respectively, with the tenth question examining how much of an individual's vegetable consumption was from mixtures. Notably, however, this tenth question is not included in standardized calculations for fruit and vegetable consumption. Using these calculations, the researcher was able to determine whether the college student was consuming < two cups of fruit and < three cups of vegetables daily. College students deemed eligible were then asked to complete baseline testing.

Baseline testing began with a demographic survey after which each participant completed a series of questionnaires assessing Social Cognitive Theory- and Self-Determination Theory psychosocial constructs. Next, participants' height, weight, and body fat percentage were measured, with performance of the YMCA 3-Minute Step Test completed thereafter. After completing the preceding testing, the researcher explained to each participant the need to wear the ActiGraph Link accelerometer for seven days during all waking hours—providing each participant with a wear log for use in tracking accelerometer wear which also contained the wear instructions (see Appendix I). Finally, each participant was given a tutorial by the researcher regarding how to input their previous day's food into the ASA24 Food Recall site. This tutorial took approximately 10 minutes, with the researcher walking through the input of one actual meal eaten by the participant during the prior day. Participants were subsequently informed that three ASA24 Food Recalls would be sent out over the next seven days. Notably, when sending out email requests to each participant to fill out the ASA24 Food Recall, the researcher

included detailed instructions and the ASA24 Food Recall's quick help guide on how to complete each survey, with a request that the participants contact the researcher if they did not feel confident in filling out the Recall(s) or a problem arose while inputting foods/beverages. Appendix K contains the previously referenced email.

Experimental Group: Polar M400 + Facebook Group. Following the assessment of physical activity, physiological, psychosocial, and dietary outcomes during baseline testing, participants randomized into the experimental group received a Polar M400 smartwatch to wear throughout the duration of the study. The Polar M400 is one of the most advanced commercially-available smartwatches, with a built-in triaxial accelerometer and GPS for tracking an individual's physical activity levels while also possessing the ability to track heart rate (via a chest-mounted heart rate monitor) and sleeping patterns (Polar, 2017). Notably, the daily activity time and steps per day tracking functions of the Polar M400 are the only metrics of interest in the current study as it pertained to validation analyses. While energy expenditure was also of interest to the researcher initially, the ActiGraph Link and associated ActiLife software only calculates physical activity-related energy expenditure—a fact confirmed with the ActiGraph Corporation while conducting the current study. This differs from the Polar M400 which accounts for an individual's resting metabolic rate (determined via the user's age, weight, and gender) *and* physical activity-related energy expenditure. Moreover, given the minute-by-minute stepping rate analysis method by which the physical activity data had to be analyzed due to the ActiGraph Link's lack of validated cut points, energy expenditure data was not available for this criterion device. Thus, a validity and

reliability comparison between the two devices' energy expenditure measurements was not possible.

Experimental group participants also received the Polar M400's user manuals/accessories and were provided a detailed instructional session detailing the use of this device and relevant features. After being instructed on the use of the Polar M400, experimental group participants were placed within a Facebook group wherein health education tips were posted twice weekly for 12 weeks. In detail, participants were asked to read one physical activity-related health education tip each Monday and one nutrition-related health education tip each Thursday throughout the study's duration. All physical activity- and nutrition-related health education tips were empirically-based and written with specific Social Cognitive Theory and Self-Determination Theory psychosocial construct(s) in mind. As one example, to increase physical activity self-efficacy and self-determination while concurrently decreasing barriers for physical activity participation, participants were informed that three 10-minute bouts of physical activity daily completed $\geq$ five days weekly is sufficient to meet national recommendations. Other health education tips aimed to improve participants' outcome expectancy and competence for health behaviors like eating more fruits and vegetables by informing participants about cheaper ways in which to purchase these foods at the grocery store and what components to examine on a nutrition label to ensure the healthiest option is being selected. These health education tips and the associated Social Cognitive Theory- and Self-Determination Theory-related psychosocial constructs targeted are outlined in Appendix L. Participants were encouraged to implement the health education tips as

much as possible and congruent with their lifestyle.

Validity of the Polar M400 during free-living conditions was assessed by comparing the degree of similarity between health metric data provided by the Polar M400 and ActiGraph Link for the six and 12 week testing sessions, while reliability of the Polar M400's health metric data was evaluated by examining the within-person stability of participants' Polar M400 health metric data between the six week and 12 week testing sessions. To facilitate these analyses, experimental participants were asked to wear the Polar M400 and ActiGraph Link accelerometer on the same wrist during all waking hours during the seven-day testing periods at six weeks and 12 weeks. Notably, participants were asked to ensure that both devices were put on and taken off at the same time in the morning and evening, respectively, in addition to brief periods throughout the day during which the devices might need to be put on and taken off (e.g., showering), with all the preceding directives outlined on each participant's wear log. Upon the participants' return to the Lab to drop off the ActiGraph Link, the researcher used each participant's Polar M400's "Diary" function to record total daily activity and steps per day for all seven days. The Polar M400 was then returned to the participant for continued use. These health metric data from the Polar M400 were subsequently compared to the identical health metric data acquired from each participants' Actigraph Link accelerometer.

Comparison Group: Facebook Only Group. The comparison group completed the same physical activity, physiological, psychosocial, and dietary assessments as the experimental group. Participants in this group were also placed within a separate, but

content-identical, Facebook group as the experimental participants wherein Social Cognitive Theory- and Self-Determination Theory-related health education tips were posted twice weekly for 12 weeks; again, on Mondays and Thursdays. However, the comparison group was not allocated use of the Polar M400 and was asked to abstain use of any other activity tracker throughout the duration of the 12-week health education intervention.

Worth mentioning is the fact that intervention fidelity protocol was also employed throughout the study to provide the greatest likelihood for intervention effectiveness. Specifically, in addition to the health education intervention adherence tracking procedures outlined previously, the researcher employed the following procedures to ensure participants within one or both groups remained engaged in the intervention: (a) experimental group participants received an extensive tutorial regarding how to operate the Polar M400 in addition to receiving the smartwatch's operating manual; (b) both groups received a tutorial of their respective Facebook page as well as a detailed review of how to report previous day's food intake using the ASA24 Food Recall—subsequently provided with reporting instructions within each emailed Recall request; (c) both groups received detailed accelerometer wear instructions and an associated accelerometer wear log to ensure adherence to ActiGraph Link wear at baseline, six weeks, and 12 weeks; (d) an Excel Spreadsheet was used to map out the exact dates of all data collection sessions and track each participant's completion of different intervention assessments (e.g., completion of ASA24 Food Recalls) so as to allow for reminders to be sent out to participants not completing study-related assessments; and (e) both groups received

separate, but nearly identical, emails during the third week and ninth weeks thanking them for participating in the study and encouraging continued intervention adherence, with the only difference between group emails being a request for the experimental group to wear the Polar M400 (see Appendix O). It is also noteworthy that the researcher used the request to schedule the six week and 12 week testing sessions to also encourage continued intervention adherence and, for the experimental group, continued Polar M400 wear. Both groups received a \$10 cash incentive after completion of each testing period (i.e., baseline testing and testing during the sixth and 12th weeks; \$30 total).

Statistical Analyses

Statistics for Study Aim #1: Effectiveness and Use/Acceptability

Descriptive statistics (i.e., means, standard deviations) for each dependent variable were first calculated for each time point, with outlier analyses performed concurrently. Second, chi-square and independent *t*-tests assessed differences in baseline characteristics between the experimental and comparison participants for all demographic and dependent variables. Third, a series of five repeated measures ANOVAs (Within-subjects factor: time; Between-subjects factor: group) examined differences in objectively-measured physical activity levels and self-efficacy, enjoyment, outcome expectancy, barriers, social support, and intrinsic motivation in addition to cardiorespiratory fitness (i.e., mean post-step test heart rate), body composition, and nutritious eating behaviors (i.e., daily kcaloric consumption, fruit and vegetable intake, whole grain consumption, and sugar-sweetened beverage consumption) between the two groups over time. For each of the preceding

analyses, partial eta-squared (η_p^2) was calculated as a measure of effect size, with small, medium, and large effect sizes designated as 0.10, 0.25, and 0.40, respectively (Richardson, 2011). Notably, a chi-square test was used to evaluate the difference between groups in participants' normative cardiorespiratory fitness category movement between baseline and 12 weeks—an approach which has been used in other research evaluating baseline to post-intervention categorical changes (Pope, Lewis, & Gao, 2015). Finally, quantitative use/acceptability data was evaluated descriptively, with qualitative data examined via a thematic analysis (Cresswell, 2007).

Statistics for Study Aim #2: Validity, Precision/Bias, and Reliability

Data output from the Polar M400 was compared to identical data from participants' ActiGraph Link accelerometers to determine the validity and reliability of the Polar M400's measurements of daily activity time and steps per day.

Validity

Initial associations between health metric data provided by the Polar M400 and Actigraph Link were assessed using intraclass correlation coefficients, with Pearson's correlation coefficients calculated (Thomas, Nelson, & Silverman, 2011d). Weak, moderate, and strong correlations were categorized as r values of 0.20-0.39, 0.40-0.59, and 0.60-0.79, respectively, with r values ≤ 0.19 classified as very weak and r values ≥ 0.80 classified as very strong (Thomas, Nelson, & Silverman, 2011e). Significantly correlated associations between the Polar M400 and Actigraph Link data output were further examined for validity using dependent t -tests (Thomas, Nelson, & Silverman,

2011b). Non-significance of the dependent *t*-tests indicated greater validity of the measurements provided by the Polar M400 (i.e., smaller differences between health metric data provided by the Polar M400 and ActiGraph Link).

Precision and Bias

The same inter-device comparisons made when conducting dependent *t*-tests were also examined via the construction of Bland-Altman plots, akin to other smartwatch validation studies conducted in free-living settings (Tully, McBride, Heron, & Hunter, 2014) and, more generally, accelerometer device validation studies (Helmerhorst, Brage, Warren, & Ekelund, 2012; Peters, Heelan, & Abbey, 2013). Bland-Altman plots were constructed with the mean of the estimates $((\text{criterion} + \text{comparison})/2)$ on the x-axis and difference between estimates $(\text{criterion} - \text{comparison})$ on the y-axis. Bland-Altman plots allowed for examination of the agreement between data output from the Polar M400 and ActiGraph Link in addition to the assessment of the bias/precision of the devices by observing how the data points were distributed about the plots (Altman & Bland, 1983). Briefly, greater agreement/precision and less bias of the measurements is observed when any given Bland-Altman plot does not demonstrate any distinct patterns among the data points. Further, to not rely exclusively on a visual examination of Bland-Altman plots in determining the bias and precision of the inter-device comparisons, linear regression analyses were performed, with the independent variable being the mean of the estimates and the dependent variable being the difference between estimates. Non-significant linear regressions are desired as this result indicates less proportional bias and greater precision between the two devices measurements (Giavarina, 2015)—results indicative that, in

comparison to the criterion Actigraph Link, the health metric data provided by the Polar M400 is more precise. Finally, further assessment of device precision was completed via calculation of coefficients of variation using the following equation: $[(\text{standard deviation of device mean for a given variable} / \text{mean of device mean for a given variable}) * 100]$. Coefficients of variation $\leq 10\%$ were classified as “good”, 10.1% - 20% categorized as “moderate”, and $> 20\%$ considered “poor” (Stokes, 1985). Coefficients between the ActiGraph Link and Polar M400 were then compared.

Reliability

Test-retest reliability assessed the stability of the Polar M400’s health metric data over time. Specifically, test-retest reliability was calculated via an examination of the within-person consistency of the Polar M400 health metric data over time (Thomas, Nelson, & Silverman, 2011c). Akin to the previously outlined validity analyses, intraclass correlations were used to assess test-retest reliability. However, instead of comparing the overall similarity of health metric data provided by the Polar M400 and ActiGraph Link, the consistency of within-person Polar M400 health metric data between the sixth and 12th weeks of the study were compared. As observed in previous literature examining the test-retest reliability of accelerometer devices using intraclass correlation coefficients (Dahlgren, Carlsson, Moorhead, Hager-Ross, & McDonough, 2010), criteria for evaluating the strength of the reliability coefficients was categorized as follows: very high reliability – r : 0.90 - 1.0; high reliability – r : 0.70 - 0.89; moderate reliability – r : 0.50 - 0.69; weak reliability – r : 0.26 - 0.49; and not reliable – r : 0.00 - 0.25.

Chapter Four: Results

In total, 80 professors were directly contacted across the study University's campus for study recruitment assistance, with 28 professors/instructors agreeing to electronically share the study's flyer with their class(es) and/or allow the researcher to come into the class to give a study recruitment speech. Summing the enrollment numbers for the classes which received the study's flyer and/or observed the researcher's recruitment speech, 3,726 students saw the study's advertisement. Additionally, the University's School of Kinesiology listservs were used to further increase the likelihood students would see the recruitment calls which, per School of Kinesiology listserv information, allowed for an additional 731 students to be contacted. Notably, however, as several professors within the School of Kinesiology agreed to assist the researcher with recruitment, the students contacted via School listservs may not have been mutually exclusive from students in the classes contacted/spoken to. Finally, paper flyers were distributed as well.

One-hundred twenty-six college students contacted the researcher with interest in study participation (2.8% reach; $[126 \div 4,457] * 100$), with 60 students subsequently scheduled for baseline screening. During baseline screening, 40 students were deemed eligible for study participation. However, two students declined study participation within 48 hours of the initiation of the week-long baseline testing period citing class schedules too busy for study participation. Thus, 38 students (28 female; $\bar{X}_{\text{age}} = 21.5 \pm 3.4$ years; $\bar{X}_{\text{height}} = 170.7 \pm 6.4$ cm; $\bar{X}_{\text{weight}} = 71.2 \pm 13.7$ kg) were randomized into an intervention or comparison group. Figure 4-1 includes a CONSORT Flow Diagram of participant flow through the study. Retention rate was 92.1%, with three experimental group participants

dropping out. Specifically, one male student discontinued participation three weeks into the study citing a full class and work schedule. The other two dropouts were female students. One of the ladies came down with appendicitis the same day as she initiated her 6th week testing period while the other was hospitalized for tonsillitis the day before she was scheduled for 12 week testing. After discussions with both ladies, both decided (understandably) to drop out of the study to recover. Comparisons of these three dropouts' baseline characteristics with that of completers did not reveal any significant differences. Given the non-significance of the three dropouts' data, an intent-to-treat analysis was employed. Of note, intent-to-treat analyses are advocated by the CONSORT guidelines (Schulz et al., 2010) and allow for trends to reflect what might happen in the real-world (i.e., the true treatment effect; Gupta, 2011) given that all participants' data are included. Pragmatically, the researcher was aware of the lower statistical power present in these analyses due to the smaller sample size and thought it best to not "throw away data". Finally, as suggested by Pedersen et al. (2017), multiple imputation was used to replace these dropouts' missing data as well as any missing data present for completers. Multiple imputation involved the creation of five new data sets, each with a regression-based predicted value of any missing data point. The pooled estimate of these predicted values was then used in further analyses. This statistical method for handling missing data is considered the best approach to ensure imputed values are precise and valid within public health interventions, with little upward or downward bias of the standard errors obtained when imputing missing data values (Pedersen et al., 2017). It should be noted, however, that among the 35 study completers, little missing data was present in the

current investigation, with the following percentages of missing data observed: physical activity outcomes: 7.1% (10 study completers did not wear the accelerometer for the requisite daily duration and/or number of days, with this situation arising for 3 participants at baseline, 3 participants at six weeks, and 4 participants at 12 weeks); physiological outcomes: 0.7% (one body fat percentage measurement would not register); psychosocial outcomes: 0.0% (the researcher hand checked each questionnaire before each participant left the Lab); and dietary outcomes: 7.3% (23 of the expected 315 [i.e., 35 participants * 9 recalls each] ASA24 Food Recalls requested from study completers were not completed).

Figure 4-1. CONSORT Study Participant Flow Diagram

Baseline Comparisons

College students' baseline demographic, physical activity, physiological, psychosocial, and dietary measurements are presented in Table 4-1. Only a single baseline difference between groups was observed for whole grain consumption, $t = 2.3$, $p = 0.03$, as the experimental group had higher whole grain consumption than the

comparison group (experimental: 1.2 ± 0.9 ounce equivalents; comparison: 0.6 ± 0.7 ounce equivalents). Overall, however, baseline comparisons suggested adequate randomization procedures.

Table 4-1. Baseline Sample Characteristics

	Experimental (<i>n</i> = 19)	Comparison (<i>n</i> = 19)	<i>p</i>-Value
Sex:			
• <i>Female</i>	15	13	0.71
• <i>Male</i>	4	6	
Race/Ethnicity			
• <i>Non-Hispanic White</i>	16	11	0.20
• <i>Asian</i>	2	6	
• <i>Other</i>	1	2	
Age (years)	21.2 ± 4.0	21.8 ± 2.8	0.58
Height (cm)	171.5 ± 3.9	170.0 ± 8.2	0.48
Weight (kg)	73.4 ± 11.3	69.0 ± 15.8	0.33
Body Mass Index	24.9 ± 3.3	23.8 ± 4.6	0.39
Body Fat %	27.7 ± 8.0	26.4 ± 7.0	0.61
Cardiorespiratory Fitness (BPM)	104.2 ± 19.1	112.5 ± 22.7	0.23
Cardiorespiratory Fitness Category:			
• <i>Very Poor</i>	3	5	0.47

<ul style="list-style-type: none"> • <i>Poor</i> • <i>Below Average</i> • <i>Average</i> • <i>Above Average</i> • <i>Good</i> • <i>Excellent</i> 	1	2	
	3	3	
	1	3	
	2	3	
	8	2	
	1	1	
MVPA/Day (min)	6.1 ± 7.0	5.8 ± 5.9	0.90
LPA/Day (min)	180.7 ± 30.7	161.6 ± 50.8	0.17
SB/Day (min)	534.7 ± 30.3	553.6 ± 50.3	0.18
Steps/Day (min)	10637.4 ± 2176.2	9268.0 ± 2098.6	0.15
Self-Efficacy	2.3 ± 0.4	2.2 ± 0.8	0.78
Social Support	2.1 ± 0.5	2.2 ± 0.9	0.69
Enjoyment	2.4 ± 0.4	2.3 ± 0.5	0.57
Barriers	27.2 ± 5.0	30.0 ± 5.7	0.11
Outcome Expectancy	9.9 ± 1.8	9.5 ± 2.3	0.53
Intrinsic Motivation	4.5 ± 1.0	4.5 ± 1.3	0.89
Daily Caloric Consumption	1986.1 ± 461.9	1953.4 ± 526.5	0.84
Daily Fruit Intake (cups)	0.8 ± 0.5	0.8 ± 0.7	0.73
Daily Vegetable Intake excluding	1.3 ± 0.6	1.2 ± 0.9	0.53

Legumes (cups)			
Daily Vegetable Intake Including Legumes (cups)	1.5 ± 0.7	1.3 ± 0.7	0.48
Daily Whole Grain Intake (oz. equivalents)	1.2 ± 0.9	0.6 ± 0.7	0.03
Daily Sugar-Sweetened Beverage Intake (cups)	1.2 ± 0.3	1.3 ± 0.4	0.45
Daily Sugar-Sweetened Beverage Intake (kcal)	110.1 ± 32.5	128.0 ± 42.9	0.48

Note. All categorical variable values are frequency; All continuous variable values are Mean $\pm$ Standard Deviation; MVPA: Moderate-to-Vigorous Physical Activity; LPA: Light Physical Activity; SB: Sedentary Behavior; kcal: calories; min: minutes.

Results for Study Aim #1: Effectiveness and Use/Acceptability

Primary Outcome

Physical Activity Changes over Time

Descriptive statistics for college students' mean daily moderate-to-vigorous physical activity, light physical activity, and sedentary behavior durations as well as steps per day are presented by group at baseline, six weeks, and 12 weeks in Table 4-2. No significant interaction or main effects were observed for any of these outcomes.

However, a trend toward a significant main effect for time, $F(2, 72) = 2.6$, $p = 0.08$; $\eta_p^2 = 0.07$, was observed for moderate-to-vigorous physical activity as both groups

demonstrated increased moderate-to-vigorous physical activity duration at six and 12 weeks versus baseline. Specifically, 4.2- and 1.6-minute increases in moderate-to-vigorous physical activity were observed for the experimental and comparison groups, respectively, at six weeks. Yet, this differential increase between groups from baseline to six weeks was not significant ($p > 0.05$). Further, although both groups demonstrated decreased moderate-to-vigorous physical activity from the sixth week to the 12th week (experimental: 2.2-minute decrease; comparison: 0.7-minute decrease), the mean duration for both groups was still higher than observed at baseline and not significantly lower than observed at six weeks ($p > 0.05$).

Table 4-2. Descriptive Statistics for Physical Activity Outcomes by Group at Baseline, 6 Weeks, and 12 weeks

Variable	Group	Baseline	6 Weeks	12 Weeks	p-Value
MVPA/Day (min)	<i>Experimental</i>	6.1 ± 7.0	10.3 ± 6.5	8.1 ± 5.6	0.08 ^a
	<i>Comparison</i>	5.8 ± 5.9	7.4 ± 5.3	6.7 ± 6.1	
LPA/Day (min)	<i>Experimental</i>	180.7 ± 30.7	162.4 ± 30.3	164.2 ± 43.1	0.16
	<i>Comparison</i>	161.6 ± 50.8	166.1 ± 63.7	175.5 ± 51.2	
SB/Day (min)	<i>Experimental</i>	534.7 ± 30.3	549.0 ± 29.2	548.7 ± 44.6	0.18
	<i>Comparison</i>	553.6 ± 50.3	559.9 ± 52.4	538.9 ± 50.3	
Steps/Day	<i>Experimental</i>	10637.4 ± 2176.2	10025.6 ± 1412.6	10085.2 ± 2108.7	0.30
	<i>Comparison</i>	9628.0 ± 2098.6	9817.5 ± 2303.5	10277.0 ± 2134.9	

Note. All values are Mean $\pm$ Standard Deviation; MVPA: Moderate-to-Vigorous Physical Activity; SB: Sedentary Behavior; kcals: kcalories; min: minutes;

^a*p*-value represents significant (or trend toward a significant) main effect of time.

Secondary Outcomes

Physiological Changes over Time

Table 4-3 presents descriptive statistics for all physiological outcomes by group at baseline and 12 weeks. Observations did not reveal any significant interaction effects for group over time. A significant main effect for time was observed, however, for body fat percentage, $F(1, 36) = 5.8, p = 0.02; \eta_p^2 = 0.14$, with the experimental and comparison groups experiencing body fat percentage increases of 2.2% and 0.3%, respectively. Notably, the experimental group's larger increase versus comparison resulted in a trend toward a significant interaction effect for group over time, $F(1, 36) = 2.9, p = 0.10; \eta_p^2 = 0.08$, for this outcome. Interestingly, however, when examining weight changes over time, slightly decreased weight in both groups was observed (experimental: - 0.6 kg; comparison: - 0.5; p for time trend > 0.05). Finally, while the changes were not statistically significant, heart rate values used as a proxy for cardiorespiratory fitness revealed the comparison group had slightly improved cardiorespiratory fitness over time (3.3-beat per minute decrease in post-step test heart rate), with the experimental group demonstrating somewhat decreased cardiorespiratory fitness over the same period (1.8-beat per minute increase in post-step test heart rate). These observations are also noticeable when examining participants' progression (i.e., improved cardiorespiratory

fitness)/regression (i.e., decreased cardiorespiratory fitness) between the normative cardiorespiratory fitness categories for each group from baseline to 12 weeks—changes depicted in Figure 4-2. Within the comparison group, two participants progressed up two normative cardiorespiratory fitness categories versus baseline, with no participant within the experimental group achieving the same outcome. Moreover, seven comparison group participants progressed up one normative cardiorespiratory fitness category, with only four experimental group participants doing the same. In fact, five and one experimental participants regressed one and two normative cardiorespiratory fitness categories, respectively, from baseline to 12 weeks. When examining baseline to 12 week changes in normative cardiorespiratory fitness categories statistically, however, no significant difference between groups was observed ($\chi^2 = 5.0, p = 0.28$).

Table 4-3. Descriptive Statistics for Physiological Outcomes by Group at Baseline and 12 Weeks

Variable	Group	Baseline	12 Weeks	<i>p</i> -Value
Weight (kg)	<i>Experimental</i>	73.4 ± 11.3	72.8 ± 9.0	0.99
	<i>Comparison</i>	69.0 ± 15.8	68.5 ± 14.7	
Body Fat %	<i>Experimental</i>	27.6 ± 8.0	29.8 ± 6.4	0.02 ^a
	<i>Comparison</i>	26.4 ± 7.0	26.7 ± 7.2	
Cardiorespiratory Fitness (Beats/Minute)	<i>Experimental</i>	104.2 ± 19.1	106.0 ± 16.9	0.18
	<i>Comparison</i>	112.5 ± 22.7	109.2 ± 20.6	

Note. All values are Mean ± Standard Deviation; %: Percentage; kg: Kilograms;

^a p -value represents significant (or trend toward a significant) main effect of time.

Figure 4-2. Normative Cardiorespiratory Category Changes over Time by Group from Baseline to 12 Weeks

Psychosocial Construct Changes over Time

No significant interaction effects for group over time were observed for any psychosocial construct. Significant main effects for time were observed, however, for self-efficacy, $F(1, 36) = 22.5, p < 0.01; \eta_p^2 = 0.38$, social support, $F(1, 36) = 8.0, p < 0.01; \eta_p^2 = 0.18$, and intrinsic motivation, $F(1, 36) = 14.2, p < 0.01; \eta_p^2 = 0.28$, such that both groups improved significantly over time on these outcomes. Moreover, a trend toward a significant main effect for time was observed for enjoyment, $F(1, 36) = 3.9, p =$

0.06; $\eta_p^2 = 0.10$, outcome expectancy, $F(1, 36) = 3.3$, $p = 0.08$; $\eta_p^2 = 0.09$, and barriers

$F(1, 36) = 3.4$, $p = 0.07$; $\eta_p^2 = 0.09$. Specifically, both groups demonstrated increased enjoyment and outcome expectancy, with decreased barriers, from baseline to 12 weeks.

Descriptive statistics are available in Table 4-4.

Table 4-4. Descriptive Statistics for Psychosocial Outcomes by Group at Baseline and 12 Weeks

Variable	Group	Baseline	12 Weeks	<i>p</i> -Value
Self-Efficacy	<i>Experimental</i>	2.3 ± 0.4	2.9 ± 0.5	< 0.01 ^a
	<i>Comparison</i>	2.2 ± 0.8	2.7 ± 0.9	
Social Support	<i>Experimental</i>	2.1 ± 0.5	2.8 ± 0.7	< 0.01 ^a
	<i>Comparison</i>	2.2 ± 0.9	2.5 ± 1.1	
Enjoyment	<i>Experimental</i>	2.4 ± 0.4	2.5 ± 0.3	0.06 ^a
	<i>Comparison</i>	2.3 ± 0.6	2.4 ± 0.5	
Barriers	<i>Experimental</i>	27.2 ± 5.0	26.1 ± 4.0	0.07 ^a
	<i>Comparison</i>	30.0 ± 5.7	28.0 ± 5.0	
Outcome Expectancy	<i>Experimental</i>	9.9 ± 1.8	10.5 ± 1.3	0.08 ^a
	<i>Comparison</i>	9.5 ± 2.3	9.8 ± 2.1	
Intrinsic Motivation	<i>Experimental</i>	4.5 ± 1.0	5.0 ± 1.1	< 0.01 ^a
	<i>Comparison</i>	4.5 ± 1.3	5.0 ± 1.4	

Note. All values are Mean ± Standard Deviation

^a*p*-value represents significant (or trend toward a significant) main effect of time.

Dietary Behavior Changes over Time

Table 4-5 presents descriptive statistics for all dietary variables by group at baseline, six weeks, and 12 weeks. A significant interaction effect for group over time was observed for sugar-sweetened beverage consumption amount, $F(2, 24) = 5.8, p < 0.01$; $\eta_p^2 = 0.33$, and, unsurprisingly given the strong positive relationship between the two variables, for sugar-sweetened beverage consumption calories as well, $F(2, 24) = 3.9, p = 0.03$; $\eta_p^2 = 0.25$. Specifically, while both groups demonstrated approximately similar sugar-sweetened beverage consumption amount and calories at baseline, the experimental group significantly increased the amount and calories consumed from sugar-sweetened beverages versus comparison at six weeks (1.8 ± 0.4 cups and 279.6 ± 137.7 kcalories vs. 1.0 ± 0.5 and 136.8 ± 115.3 kcalories, respectively; all $p < 0.01$). Notably, however, both groups ended with sugar-sweetened beverage consumption amounts at 12 weeks which were equal to or lower than that observed at baseline (experimental: 1.1 ± 0.3 cups; comparison: 1.3 ± 0.6 cups). Yet, sugar-sweetened beverage consumption calories was still higher at 12 weeks compared to baseline for the experimental group (147.8 ± 99.3 kcalories) but not the comparison group (110.8 ± 47.8 kcalories). Noteworthy is the fact that only six experimental group participants and eight comparison group participants reported sugar-sweetened beverage consumption across all three time points.

While no other significant interaction or main effects were observed for dietary outcomes, two other observations were noted. First, a trend toward a significant interaction effect for group over time was observed for vegetable consumption including

legumes, $F(2, 72) = 2.9, p = 0.06$; $\eta_p^2 = 0.07$, and, given these outcomes' strong positive relationship, vegetable consumption excluding legumes, $F(2, 72) = 2.8, p = 0.07$; $\eta_p^2 = 0.07$. Interestingly, for vegetable consumption including legumes, comparison participants demonstrated increased consumption at six weeks, with the experimental group experiencing slight declines in consumption over the same time period. Yet, at 12 weeks, the comparison group had experienced decreased vegetable consumption including legumes to levels below that observed at baseline while the experimental group remained stable at consumption amounts equal to that observed at six weeks. Predictably, similar trends by group over time were observed for vegetable consumption excluding legumes. Second, and finally, both groups demonstrated consistently decreased daily caloric consumption at six and 12 weeks (overall decreases - experimental: -41.0 kcalories; comparison: -143.3 kcalories).

Table 4-5. Descriptive Statistics for Dietary Outcomes by Group at Baseline, 6 Weeks, and 12 Weeks

Variable	Group	Baseline	6 Weeks	12 Weeks	<i>p</i> -Value
Daily Caloric Consumption	<i>Experimental</i>	1986.1 ± 461.9	1971.7 ± 553.4	1945.1 ± 569.6	0.80
	<i>Comparison</i>	1953.4 ± 526.5	1935.3 ± 478.0	1810.1 ± 512.6	
Daily Fruit Intake (cups)	<i>Experimental</i>	0.8 ± 0.5	0.8 ± 0.5	1.0 ± 0.9	0.22
	<i>Comparison</i>	0.8 ± 0.7	0.6 ± 1.6	0.6 ± 0.7	

Daily Vegetable Intake Excluding Legumes (cups)	<i>Experimental</i>	1.3 ± 0.6	1.3 ± 0.7	1.3 ± 0.5	0.07
	<i>Comparison</i>	1.2 ± 0.7	1.5 ± 0.9	0.8 ± 0.5	
Daily Vegetable Intake Including Legumes (cups)	<i>Experimental</i>	1.5 ± 0.7	1.3 ± 0.7	1.3 ± 0.5	0.06
	<i>Comparison</i>	1.3 ± 0.7	1.7 ± 1.0	1.0 ± 0.6	
Daily Whole Grain Intake (oz. equivalents)	<i>Experimental</i>	1.2 ± 0.9	1.1 ± 0.8	1.1 ± 0.9	0.32
	<i>Comparison</i>	0.6 ± 0.7	1.0 ± 0.9	0.8 ± 1.0	
Daily Sugar-Sweetened Beverage Intake (Cups)	<i>Experimental</i>	1.2 ± 0.3	1.8 ± 0.4	1.1 ± 0.3	< 0.01
	<i>Comparison</i>	1.3 ± 0.4	1.0 ± 0.5	1.3 ± 0.6	
Daily Sugar-Sweetened Beverage Intake (kcal)	<i>Experimental</i>	110.1 ± 32.5	279.6 ± 137.7	147.8 ± 99.3	0.03
	<i>Comparison</i>	128.0 ± 42.9	136.8 ± 115.3	110.8 ± 47.8	

Note. All values are Mean ± Standard Deviation;

^a*p*-value represents significant (or trend toward a significant) main effect of time.

Adherence to the Intervention

Combined, both groups demonstrated high adherence to Facebook-delivered health

education intervention: $87.1 \pm 21.9\%$. When stratified by group, it was found that the comparison group demonstrated lower adherence ($84.4 \pm 22.3\%$) to the health education intervention than the experimental group ($89.8 \pm 21.8\%$).

Intervention Use/Acceptability

Participants reported the Facebook health education tips to be between “somewhat helpful” to “helpful” (5.4 ± 1.2 on 7-point Likert scale), with the comparison group finding these health education tips marginally more helpful (5.5 ± 0.5) than the experimental group (5.4 ± 1.6). As for implementation of the health education tips, all participants combined reported implementing these tips between “two times per month” and “one to three times per week” (3.4 ± 1.2 on 6-point Likert scale). Both the experimental and comparison group reported nearly identical health education tip implementation frequency (3.5 ± 0.7 and 3.4 ± 1.6 , respectively). Notably, only one participant in either group engaged in Facebook group activity beyond “Liking” the health education tips—commenting on her agreement with the nutrition-related health education tip posted for that date.

Additional comments gathered from experimental group participants observed these participants to believe the Polar M400 smartwatch to be between “somewhat useful” to “useful” in assisting them in becoming more active (5.4 ± 1.4 on 7-point Likert scale), with ease-of-use reported as “somewhat easy” (5.4 ± 1.5 on 7-point Likert scale). Experimental group participants stated the positive features of the Polar M400 to be: the “exercise bar” on the main screen; the physical inactivity reminder; the diary function; the total calorie calculation (i.e., resting metabolic rate + physical activity energy

expenditure) as opposed to only physical activity-related energy expenditure; competing with other smartwatch users (not in study) to get the “most steps”; and the capability of the smartwatch to track numerous physical activity modalities. Despite the positive features outlined, participants stated the following improvements should occur to the Polar M400: smartphone syncing process/capability needs improvement as syncing to the smartphone application and computer software was time-consuming and difficult; size of the watch (i.e., needs to be smaller); needs built-in heart rate monitor; was not as intuitive as other smartwatches; and GPS was sometimes poor for outdoor activities.

Results for Study Aim #2: Validity, Precision/Bias, and Reliability

Table 4-6 presents the descriptive statistics for the Polar M400 and ActiGraph Link for daily activity time and steps per day.

Table 4-6. Descriptive Statistics for Polar M400 Daily Activity Time and Steps per Day vs. ActiGraph Link

	Polar M400	ActiGraph Link
Daily Activity Time (min)	262.7 ± 39.5	195.5 ± 32.8
Steps per Day	10329.5 ± 2528.5	11090.4 ± 1585.5

Note. All values are Mean ± Standard Deviation

Validity

Table 4-7 presents intraclass correlations between the Polar M400 and ActiGraph Link for daily activity time and steps per day. The correlations indicated strong

associations between the Polar M400 and ActiGraph Link for both metrics. Subsequent dependent t -tests revealed that while the Polar M400 did tend to underestimate steps per day, this smartwatch does possess marginal initial validity for the measurement of this health metric versus the ActiGraph Link, $t = 1.9$, $p = 0.08$. Yet, when compared to the ActiGraph Link, the Polar M400 did not demonstrate an ability to validly measure daily activity time, $t = -9.4$, $p < 0.01$ —often overestimating this metric.

Table 4-7. Intraclass Correlations between Polar M400 Daily Activity Time and Steps per Day and the ActiGraph Link

	Actigraph Link	
Polar M400	0.64**	0.72**
	Daily Activity Time (Min)	Steps per Day

Note. **indicates significant correlation at $p < 0.01$ level

Precision and Bias

Bland-Altman plots comparing daily activity time and steps per day for the Polar M400 and ActiGraph Link can be viewed in Figure 4-3 and Figure 4-4, respectively. Notably, when interpreting the Bland-Altman plots, readers should keep in mind that the ActiGraph Link was used as a reference device when the mean differences between device measurements of daily activity time and steps per day were calculated—per standard validation procedures (Peters et al., 2013). Therefore, Figure 4-3 includes negative numbers on the y-axis given that the ActiGraph Link had *lower* mean daily activity time measurements than the Polar M400. Conversely, the numbers on Figure 4-

4's y-axis are often positive as the ActiGraph Link had *higher* mean steps per day measurements than the Polar M400.

In examining Figure 4-3, no notable trends in the data points were discernable for Polar M400 daily activity time measurements—indicative of little measurement bias. This observation was corroborated by a follow-up non-significant linear regression analysis, $F(1, 18) = 1.0, p = 0.34$. That said, it is notable that this commercially-available device consistently overestimated daily activity time, with wide limits of agreement for these differences observed (95% CI: -6.5, -129.9 minutes; ActiGraph Link was reference so negative CI indicates overestimation by Polar M400). Examination of Figure 4-4 indicated that Polar M400 steps per day measurements had some measurement bias, with lower means steps per day resulting in greater underestimation of this metric by the Polar M400. Although this bias is difficult to surmise from examination of Figure 4-4 given the plot's scaling, the measurement bias was confirmed by a significant linear regression, $F(1, 18) = 8.4, p = 0.01$, and limits of agreement for the devices' steps per day measurement differences which are more pronounced for underestimation than overestimation (95% CI: 4,211.3, -2689.5 steps; ActiGraph Link was reference so more positive CI indicates greater underestimation by Polar M400). Finally, further examination of precision via calculation of coefficients of variation revealed similar moderate precision of the ActiGraph and Polar M400 for daily activity time, but not for steps per day as the Polar M400 had higher variability (i.e., less precision) in these measurements than observed for the ActiGraph Link. These data are available in Table 4-8 and provide further support for the Bland-Altman analyses.

Figure 4-3. Bland-Altman Plot Comparing the ActiGraph Link and Polar M400

Daily Active Time Measurements

Figure 4-4. Bland-Altman Plot Comparing the ActiGraph Link and Polar M400**Steps per Day Measurements****Table 4-8. Coefficients of Variations for Polar M400's Daily Active Time and Steps per Day vs. ActiGraph Link**

	Polar M400	ActiGraph Link
Daily Activity Time	$\pm 16.3\%$	$\pm 16.9\%$
Steps per Day	$\pm 30.7\%$	$\pm 14.6\%$

Reliability

Test-retest reliability coefficients between the Polar M400 and ActiGraph Link daily activity time and steps per day measurements are available in Table 4-9. The Polar M400 demonstrated poor test-retest reliability for daily activity time ($r = 0.15$, $p = 0.55$) but possessed moderate test-retest reliability for steps per day ($r = 0.54$, $p = 0.02$).

Table 4-9. Test-Retest Reliability Coefficients for Polar M400 Daily Active Time and Steps per Day

	Polar M400
Daily Activity Time	0.15
Steps per Day	0.54*

Note. *Indicates significance at $p < 0.05$ level.

Chapter Five: Discussion

Akin to the results above, the following discussion was split into two subsections. First, the researcher discussed observations made regarding the intervention's effectiveness at promoting improved physical activity, physiological, psychosocial, and dietary outcomes. Additional discussion was also given to participants' statements regarding the interventions' use/acceptability, with connections drawn between these statements and the intervention's effectiveness when relevant. Throughout this first subsection the practical implications the study's observations have for the use of this type of technology-based intervention among college students and other populations is discussed, with concluding remarks containing this commentary too. Second, observations regarding the validity, precision/bias, and reliability of the Polar M400 smartwatch are discussed, with these observations also practically applied to real-world settings and the reservations which might need to be kept in mind when interpreting the Polar M400's health metric data. Notably, both sections consistently relate this study's observations to previous literature. Finally, the discussion section concludes with an overview of the study's strengths and limitations. Of note, after each listed limitation of the current study and throughout the discussion, the researcher has highlighted future research directions.

Discussion for Study Aim #1: Intervention Effectiveness and Use/Acceptability

This study's first purpose was first to investigate the effectiveness of using the Polar M400 smartwatch in combination with a Social Cognitive Theory- and Self-

Determination Theory-based, Facebook-delivered health education intervention in the promotion of college students' physical activity and nutritious eating behaviors over 12 weeks. Specifically, experimental group participants received a Polar M400 smartwatch and were enrolled in a Facebook group wherein physical activity- and nutrition-related health education tips predicated upon the Social Cognitive Theory and Self-Determination Theory were delivered via twice-weekly posts. Experimental group participants' physical activity, physiological, psychosocial, and dietary outcomes were compared to those of comparison group participants who were included only in a separate, but content-identical Facebook group. Broadly, it was hypothesized that experimental group participants would demonstrate greater beneficial changes over time in the preceding outcomes than comparison participants. Observations suggested that while the experimental group did have slightly greater increased moderate-to-vigorous physical activity over time, the combined use of the Polar M400 smartwatch and a theoretically-grounded, Facebook-delivered health education intervention may not offer any advantages versus comparison. Indeed, similar magnitudes of improvement were observed between groups for weight and all psychosocial variables, with trends in most other variables similar between groups too. Detailed discussion of each of these observations is included below.

Observations regarding the effectiveness of the current smartwatch-based health behavior change intervention in promoting increased physical activity demonstrated partial agreement with the study's first hypothesis for study aim one as both groups demonstrated increased moderate-to-vigorous physical activity from baseline to six

weeks, with this increase approximately two and a half minutes higher among experimental group participants over this time period versus comparison. Further, despite decreased moderate-to-vigorous physical activity from six weeks to 12 weeks, both groups still concluded the intervention with greater moderate-to-vigorous physical activity duration at 12 weeks than observed at baseline.

Cadmus-Bertram and colleagues (2015a, 2015b) observed significantly increased moderate-to-vigorous physical activity and steps per day over 16 weeks among postmenopausal women using a Fitbit to track daily physical activity, with smaller non-significantly increased moderate-to-vigorous physical activity and steps per day observed among controls. Further, another study by Thorndike et al. (2014) did find slight increases in physical activity among medical residents provided a Fitbit during a 12-week intervention versus no change among controls. While the increased moderate-to-vigorous physical activity observed among the current study's experimental group participants was smaller in magnitude compared to Cadmus-Bertram et al.'s observations (4.2-minute per day vs. 8.9-minute per day increase, respectively), the current investigation's observations are stronger than that of Thorndike et al. and better than observations made during other smartwatch-based randomized trials. For example, smartwatch use resulted in either null (Wang et al., 2015) or negative effects (Thompson et al., 2014) on physical activity in previous studies. As stated, limitations within the preceding studies included the lack of a sound theoretical basis despite theory's importance in health behavior change (Simons et al., 2018), the absence of a nutrition element, inadequate intervention fidelity protocol, and no health education component despite the importance of health

literacy in promoting proper health behaviors (Rikard et al., 2016). While the current study built upon the preceding limitations, it is also worth noting that these studies were not conducted among young adults—an age cohort more technology-savvy and likely to use technology for health promotion purposes (Partridge & Redfern, 2018; Perrin, 2015; Simons et al., 2018). Thus, it is important to compare this study’s observations with that of the paucity of prior randomized studies of smartwatch-based health behavior change interventions conducted among *college students*.

Compared to the most analogous randomized smartwatch-based health behavior change interventions conducted to date among college students, the current study’s observations regarding physical activity promotion were often more positive. For instance, Kim et al. (2018) conducted what might be viewed as the most comparable study to the current investigation. During this 15-week randomized trial, college students were provided a Misfit Flash smartwatch to track daily physical activity while also being concurrently enrolled in a 20-class health-related course focused on increasing students’ health literacy. Students randomized into the comparison group only participated in the health literacy course. Researchers observed significantly decreased moderate-to-vigorous physical activity among the comparison group from baseline to post-intervention, with no change in this outcome over time among experimental group participants. Further, a study by Melton et al. (2016) observed no difference over time in steps per day at 6 weeks among experimental participants provided a Fitbit to track physical activity versus comparison participants using a smartphone-based fitness application (MyFitnessPal) for the same purpose. Moreover, at an 8-week follow-up, the

experimental participants in these researchers' study demonstrated significantly decreased steps per day versus comparison. Thus, the fact both groups in the current study demonstrated increased moderate-to-vigorous physical activity duration at all time points versus baseline—with the magnitude of these changes higher for experimental participants—is promising. It should be mentioned, however, that a study by Rote (2017) did indicate pedometry-assessed steps per day increased significantly (~1,100 steps) among college students enrolled in an introductory health course and using a Fitbit to track physical activity over 16 weeks. The same observations were not made within the comparison group enrolled exclusively in the health course or the control group enrolled in a humanities course. Yet, when Rote and colleagues examined the Fitbit's data, a significant decline of approximately 2,500 steps per day was observed among the experimental group. The latter finding adds skepticism to the observations of increased steps per day made by the study-related pedometer and makes it difficult to compare the current study to this prior investigation.

When considering the fact college students in the similarly-designed studies by Kim et al. and Rote required college students to enroll within in-person college health courses—which may have presented a higher participant burden to these students—it is promising that the current study observed increased moderate-to-vigorous physical activity participation among both groups. To elaborate, the fact that a low-burden, well-integrated approach was able to demonstrate initial efficacy in promoting increased physical activity participation bodes well for future interventions seeking to promote population-level changes in physical activity—particularly among younger cohorts such

as college students who are interested in using technology to track health indices (Partridge & Redfern, 2018) and access social media sites multiple times daily (Perrin, 2015). Two reasons might be postulated for the current study's observations regarding increased moderate-to-vigorous physical activity among both groups when using this lower-burden design. First, the current study developed and implemented the intervention based upon two well-researched health behavior change theories—the Social Cognitive Theory and Self-Determination Theory—with all health education content provided to participants reflecting these theories' constituent constructs. Second, and perhaps just as importantly, intervention fidelity protocol was implemented every two/three weeks to ensure high intervention adherence among both groups. As a theoretical basis and proper intervention fidelity protocol are considered important to increase the likelihood of intervention effectiveness (Borrelli, 2011; Brug et al., 2005; Patten, 2014), future low-burden interventions with the objective to increase physical activity among college students should consider including these two components regardless of the medium by which the intervention is delivered to ensure maximum intervention adherence and impact.

Despite the positive observations noted above for moderate-to-vigorous physical activity, caution is advised when interpreting these trends. This is so for two reasons. First, it should be noted these increases in moderate-to-vigorous physical activity were of small magnitude (e.g., experimental group would only engage in approximately 30 more minutes per week of moderate-to-vigorous physical activity than baseline when examining this group's sixth week measurements). Second, no previously-reviewed study

among college students sought to recruit insufficiently active samples as done in the current study. Thus, future studies might consider the following changes: (a) inclusion of more in-depth behavior change techniques aligned with the Social Cognitive Theory and Self-Determination Theory (e.g., goal setting) to possibly increase the magnitude of improved physical activity participation observed; and (b) implement inclusion criteria similar to the current study to discern whether the increased moderate-to-vigorous physical activity observed in the current study's insufficiently active cohort can be replicated. Notably, while the current study observed no changes for light physical activity, sedentary behavior, or steps per day, the durations/magnitudes of these outcomes and the associated health implications are worth discussion.

The current study's participants were observed to engage in long durations of habitual sedentary behavior (mean of approximately 547 minutes per day) and moderate durations of habitual light physical activity (mean of approximately 168 minutes per day). While striking, these observations were expected given the current study's recruitment of insufficiently active college students. Additionally, these observations agree with the smartwatch-based health behavior change intervention conducted by Kim et al. (2018) wherein participants engaged in averages of approximately 531 and 194 minutes of daily sedentary behavior and light physical activity, respectively.

Furthermore, cross-sectional studies of college students' physical activity and sedentary behaviors (Peterson et al., 2018; Smetaniuk et al., 2017) have also reported physical activity and sedentary behavior durations akin to the present study. In fact, Peterson and colleagues (2018) indicated college students engaged mean daily durations of sedentary

behavior and light physical activity of approximately 10 hours (i.e., ~600 minutes) and 3.5 hours (i.e., ~210 minutes), respectively, with Smetaniuk and associates (2017) observing masters students to demonstrate even higher mean daily durations of sedentary behavior (i.e., approximately 11 hours or 660 minutes) but similar mean durations of light physical activity (i.e., approximately 3.4 hours or 205 minutes).

Researchers within both studies pointed to the fact that college students often engage in long hours of studying and class attendance which may have contributed to the high sedentary behavior durations observed. Regardless of the explanation for the high levels of sedentary behavior observed within these studies and the present study, however, long durations of sedentary behavior can predispose an individual to several negative health consequences. Specifically, sedentary behavior demonstrates a positive relationship with cardiovascular disease (American Heart Association, 2015) and all-cause/cardiovascular disease mortality (Evenson, Wen, & Herring, 2016) while also increasing risk for development of metabolic syndrome (i.e., cooccurrence of elevated blood sugar, atypical cholesterol/triglyceride levels, increased blood pressure, and excess abdominal body fat) independent of physical activity levels and cardiorespiratory fitness (Greer, Sui, Maslow, Greer, & Blair, 2015). The latter point is particularly important when considering that while the college students in the current sample did engage in moderate levels of light physical activity and demonstrated slightly increased moderate-to-vigorous physical activity over the course of the intervention, these levels of physical activity may not be fully protective against development of conditions contributing to metabolic syndrome—particularly as the college students within both groups were still

engaging in physical activity levels below national recommendations (PAGAC, 2018, USDHHS, 2008). In light of these and other negative health consequences, calls have been made to conduct research that endeavors not only to increase physical activity, but decrease sedentary behaviors as well (Lewis, Napolitano, Buman, Williams, & Nigg, 2017). As such, future research might also tailor health education content to the reduction of sedentary behavior in addition to the promotion of physical activity—perhaps asking participants to develop plans regarding how they might reduce sedentary behavior time and increase physical activity participation. Regarding the similar moderate durations of light physical activity observed in their studies compared to the current investigation, Kim et al. (2018), Peterson et al. (2018), and Smetaniuk et al. (2017) were less clear on possible explanations for these durations of light physical activity.

One plausible explanation for the moderate durations of light physical activity observed in the current and past studies might be attributable to active transportation among college students—particularly among students attending urban Universities (Bopp, Bopp, & Schuchert, 2013; Bopp, Kaczynski, & Wittman, 2011; Sisson & Tudor-Locke, 2008). Undoubtedly, the fact the study University is located within a metropolitan area within a city that places high priority on health and providing opportunities for active transportation makes this explanation more feasible as college students in the current study were not only walking from class to class, but also often walking to and from home—a fact also reflected in the approximate 10,000 steps per day mean observed for both groups at all time points. Future studies might include physical activity diaries to delineate the sources of physical activity (e.g., active transportation, exercise, other

activities of daily living) from which different intensities and durations of physical activity are arising. Nevertheless, while light physical activity does confer some health benefits (Powell, Paluch, & Blair, 2011; PAGAC, 2018; Saint-Maurice, Troiano, Berrigan, Kraus, & Matthews, 2018), future interventions should still endeavor to increase daily moderate-to-vigorous physical activity duration given this physical activity intensity's demonstrated positive and robust effects on health outcomes (PAGAC, 2018; USDHHS, 2008). Aside from the methodological improvements the current study made compared to past literature, the present investigation also built upon limitations of past smartwatch-based health behavior change research as, unlike most prior literature, this study investigated changes in physiological, psychosocial, and dietary outcomes over time. Together, these additional observations add further evidence to suggest either type of intervention employed in the current study might be feasible to promote improved health among college students and other populations.

Examination of changes in physiological outcomes over time revealed slightly decreased weight among both groups from baseline to 12 weeks. Yet, it is interesting that both groups demonstrated increased body fat percentage during the intervention, with the comparison group experiencing somewhat improved cardiorespiratory fitness and the experimental group demonstrating slightly decreased cardiorespiratory fitness over this same time period. Taken together, these observations are incongruent with this study's second hypothesis for the study's first aim as the experimental group did not experience significantly greater improvements for these outcomes versus the comparison group, with seemingly paradoxical observations made for changes in body fat percentage and

cardiorespiratory fitness during the intervention. Compared to prior literature (Cluskey & Grobe, 2009; de Vos et al., 2015; Racette et al., 2005), however, the slightly decreased weight for both groups is notable as these studies indicated that college students can gain up to an average of 4.2 kilograms during an academic year, with these investigations indicating the steepest upward weight trajectories being the first two years of college attendance. As upward weight trajectories in young adulthood have been observed predictive of higher body mass index in middle age (Malhotra et al., 2013), weight reduction is considered important given its inverse relationship with cardiovascular disease risk (PAGAC, 2018; USDHHS, 2010) and systolic and diastolic blood pressure (Franz et al., 2015; Neter et al., 2003). Therefore, the present study's observations suggest that, regardless of provision of a smartwatch, a theoretically-grounded, social media-delivered intervention which provides easily implemented health education tips might have some efficacy in the attenuation of weight gain among college students.

Reducing body fat percentage is also important given the positive relationship of excess body fat—particularly the more metabolically-active android adipose tissue (Kenney et al., 2015b)—with diabetes and cardiovascular disease (Despres, 2012) in addition to cancer and all-cause mortality (Britton et al., 2013). Thus, while the slight reductions in body weight were encouraging, the increased body fat percentage among both groups was undesired. Three possible explanations might have contributed to this observation. First, while considered an accurate field measure of body fat percentage, it should be noted that bioelectrical impedance body fat percentage measurements have percentage errors of up to $\pm 5.1\%$ when compared to the “gold standard” measurement of

dual x-ray absorptiometry during intervention studies (Li et al., 2013)—an error which should be accounted for when interpreting the observations of this study. Second, and relatedly, bioelectrical impedance measurements are highly sensitive to body water levels and electrolyte balance (Kenney et al., 2015b). To reduce the possible error this sensitivity might have introduced, the researcher requested that the study's participants attend 12th week testing at approximately the same time of day and having consumed similar foods/beverages as at baseline. Yet, scheduling limitations made it difficult for some participants to schedule 12th week testing at an approximately identical time of day compared to baseline. Further, without a food log, it is impossible to know whether participants consumed similar foods/beverages as before baseline testing. Finally, although combined physical activity and nutritious eating interventions have proven more effective at promoting improved health outcomes than either type of intervention alone, nutritious eating interventions have demonstrated a greater likelihood of promoting beneficial changes in weight-related outcomes compared to physical activity interventions (Elliot & Hamlin, 2018). Therefore, future studies might consider a more in-depth approach to promoting physical activity and nutritious eating behaviors capable of promoting weight and, more specifically, body fat percentage loss. For instance, in addition to the theoretically-grounded, Facebook-delivered health education tips posted to this social media platform during this study, future studies might also post a weekly physical activity program along with recipes/ideas for healthy, nutrient-dense, and low-cost meals which college students could also implement at their discretion. Additionally, more accurate measures of body fat percentage (e.g., dual x-ray absorptiometry,

hydrodensiometry) might be employed in future studies as well.

The improvements in cardiorespiratory fitness observed among the comparison group, but not the experimental group, were unexpected. Large scale epidemiological studies have indicated increased cardiorespiratory fitness to be associated with reduced all-cause mortality (Kodama et al., 2009)—benefits resulting from participating in higher physical activity intensities (typically moderate or vigorous physical activity intensities capable of improving cardiovascular and respiratory function [e.g., reducing blood pressure via increased arterial elasticity, increasing oxygen perfusion efficiency to the body's exercising tissues, enhancing ability of body to remove metabolic waste products, among other adaptations]) (Kenney, Wilmore, & Costill, 2015a). Therefore, this study's cardiorespiratory fitness observations are perplexing and worth explanation.

Two reasons might be posited as to the observations made regarding cardiorespiratory fitness in the present study. First, when examining the baseline cardiorespiratory fitness of each group, it is evident that the experimental group began the study with better cardiorespiratory fitness than the comparison group. Specifically, the experimental group began the study with a mean post-step test heart rate of 104.2 beats per minute, while the comparison group's corresponding value was 112.5 beats per minute. At 12 weeks, the post-step test heart rates for the experimental and comparison groups were 106.0 and 109.2 beats per minute, respectively. These baseline to 12th week trends in cardiorespiratory fitness may suggest some regression to the mean as the comparison group experienced decreased post-step test heart rate of ~ 3 beats per minute (i.e., indicative of improved cardiorespiratory fitness) while the experimental group

demonstrated increased post-step test heart rate of ~ 2 beats per minute (i.e., indicative of reduced cardiorespiratory fitness). These observations are further corroborated when considering the fact the largest number of experimental group participants were classified into the “good” normative cardiorespiratory fitness category ($n = 8$ participants) at baseline whereas comparison participants were most frequently placed into the “very poor”, “below average”, and “average” categories ($n = 5, 3$, and 3 participants, respectively) at baseline—suggesting a possible ceiling effect might have also been present for the experimental group.

A second reason for the observations of slightly decreased cardiorespiratory fitness among the experimental group versus the comparison group might also lie in Polar M400’s capabilities compared to other smartwatches on the market. In detail, most currently available smartwatches possess light-emitting diode sensors on the back of the watch face which detect changes in the pulsatile flow of blood at the wearer’s wrist allowing continuous and real-time heart rate information to be provided (Lee & Gorelick, 2011; Lee, Gorelick, & Mendoza, 2011). The Polar M400 does not possess this feature and, instead, provides the wearer a chest-strap with a snap-on heart rate sensor which transmits the wearer’s heart rate to the smartwatch. This difference is notable as the use of a chest-mounted heart rate monitor—while amenable to some cohorts (e.g., long distance runners)—is often burdensome and perhaps inconvenient for most individuals to use during exercise much less throughout the day. As heart rate is a reliable metric of physical activity intensity (Kenney et al., 2015a) and can play a key role in ensuring individuals are participating in physical activity intensities necessary to facilitate

improved cardiorespiratory fitness, it is perhaps unsurprising that the simple act of wearing the Polar M400 did not prevent regression in cardiorespiratory fitness among experimental group participants. In fact, while the experimental group's use of the chest-mounted heart rate monitor was not tracked, noteworthy is the fact that all but two of the heart rate monitors provided to experimental group participants appeared to have been opened for use, with several experimental group participants stating the lack of a wrist-mounted heart rate monitor to be a negative aspect of the smartwatch on the use/acceptability survey. Further, the small magnitude of increase observed for moderate-to-vigorous physical activity among the experimental group was likely not nearly enough to stimulate positive cardiorespiratory fitness adaptations among this group—particularly given this group's satisfactory level of cardiorespiratory fitness observed at baseline. Nonetheless, if possible in future investigations, a $\dot{V}O_{2\text{ Max}}$ test may be performed using indirect calorimetry—considered the “gold standard” of cardiorespiratory fitness assessment—so as to allow for the determination of much smaller changes in cardiorespiratory fitness than could be determined during the current study's step test (Kenney et al., 2015a).

College students within both groups had notable increases self-efficacy, social support, and intrinsic motivation from baseline to 12 weeks. Further, over this same time period, both groups exhibited slightly increased enjoyment and outcome expectancy as well as marginally decreased barriers. While the study's third hypothesis for the study's first aim stated the experimental group would experience greater improvements in all psychosocial constructs over time versus the comparison group, these observations are

still promising given the fact many of these constructs are key determinants to improved health behavior participation, with this study representing the first known analyses of these constructs within a smartwatch-based health behavior change intervention. For simplicity and brevity, the discussion below is organized by theory—first reviewing observations among psychosocial constructs aligned with the Social Cognitive Theory (i.e., self-efficacy, social support, enjoyment, outcome expectancy, and barriers) and then discussing observations made regarding Self-Determination Theory-related intrinsic motivation. Nonetheless, every attempt has been made to highlight the interconnectedness of this study's psychosocial construct observations.

Improvements in self-efficacy were welcomed as studies have indicated this construct to explain the variance observed in physical activity changes during health behavior change interventions (Dishman et al., 2004; Sriramatr et al., 2016), with other research having indicated that college students' self-efficacy significantly predicts this cohort's participation in physical activity and nutritious eating behaviors (Mirzaei-Alavijeh et al., 2018; Von Ah et al., 2004). It is known that an individual's self-efficacy for a given behavior is associated with the individual's efficacy expectations regarding said behavior (Bandura, 1977). For instance, if an individual does not expect to be able to participate in the recommended 30 minutes of moderate-intensity physical activity daily on $\geq$ five days per week (PAGAC, 2018; USDHHS, 2008), this individual is less likely to engage in physical activity in pursuit of this recommendation. Yet, by manipulating this negative efficacy expectation, health professionals can promote positive efficacy expectations and potentially increase target behavior participation. In the present study,

increasing college students' belief that the preceding recommendation was attainable was done by indicating to participants that three 10-minute bouts of moderate-intensity physical activity daily on $\geq$ five days per week was sufficient to meet this recommendation; thus increasing college students' confidence in attaining the recommended amount of physical activity despite constraints imposed on their time by college attendance and, for some, job/personal responsibilities. Notably, while a physical activity example is presented above, identical efforts were made to improve self-efficacy (and all other psychosocial constructs) for nutritious eating (see Appendix L).

Social support from friends and other significant figures in promoting improved health behavior participation has been also observed as important among college students (Marr & Wilcox, 2015; Voorhees & Young, 2003), rendering the current study's observations of increased social support among both groups promising. Previous technology-based health behavior change interventions have observed improved social support among this population. For example, in a randomized trial conducted by Cavallo et al. (2012), researchers used a health promotion website to assist in the self-monitoring and improvement of physical activity participation while using Facebook to increase physical activity-related social support among college students. Researchers observed physical activity and social support to increase to greater degree among experimental participants—albeit non-significantly—versus comparison participants receiving only limited access to the health promotion website. These observations for social support not only agree with the trends observed between each groups' increased social support in the current study, but also demonstrate congruence with other literature which has observed

technology-based health behavior change interventions to promote improved social support (Edney et al., 2017; Maher et al., 2015). When considering the fact enjoyment has been cited as predictive of health behavior participation among college students (Deliens et al., 2015; Poobalan, Aucott, Clarke, & Smith, 2012), future combined smartwatch- and social media-based health behavior change interventions might seek to synergistically improve social support and enjoyment. Specifically, a health behavior change intervention of this type may recruit clusters of participants with pre-existing friendships as done in a previous social media-based health behavior change intervention (Maher et al., 2015) while also highlighting the enjoyable aspects (e.g., “feeling good”, “having more energy”) of physical activity participation and adherence to healthier dietary behaviors—only the latter of which was done in the current study. If employed within a study designed similarly to the present investigation, this recruitment strategy may not only improve social support to a greater degree than observed in the current study, but might also increase enjoyment for proper health behavior participation as these friends: (1) compete against one another for the “most steps” accumulated (as tracked by a smartwatch); and (2) remind one another of the enjoyable aspects/outcomes of these behaviors about which they are learning via the social media-delivered health education intervention—possibly contributing to improved outcome expectancy too.

Although the trends in outcome expectancy and barriers in the current study were small, it is encouraging that improvements in both psychosocial outcomes were observed. Recent research has indicated outcome expectancy to be a significant predictor of whether college students are meeting physical activity guidelines (Farren et al., 2017),

with more positive outcome expectancy a greater predictor of college students' initial intention to engage in health behaviors (Gao, Xiang, Lee, & Harrison Jr., 2008). Further, research on college students' perceived barriers to health behavior participation have indicated lack of time, inconvenient recreation center hours, and lack of social support to limit physical activity participation (Blake et al., 2017; Grubbs & Carter, 2002) while perceived barriers to nutritious eating behaviors have been observed as the absence of family support, lack of a daily routine, and the high cost/longer time needed to purchase ingredients/fix healthy meals (Cluskey & Grobe, 2009). When mapped onto the current study's observations, it is notable that the health education tips provided concentrated largely on *modifying* physical activity and dietary behaviors, with some attention also paid to the *acute benefits* of making these health behavior changes. While sound methodology, it is possible that greater concentration on the *chronic benefits* of participation in these health behaviors (i.e., the positive outcomes)—as opposed to a majority concentration on simply *modifying* these behaviors—may have been needed to improve outcome expectancy; a fact suggested within previous research (Gao et al., 2008; Maddux, Norton, & Stoltenberg, 1986). Similarly, while every attempt was made to draft health education tips which were congruent with the empirically-based barriers college students have reported for proper physical activity and dietary behaviors, the health education tips may have still been too “generic” and perhaps not as directive/challenging for the current study's sample. Future combined smartwatch- and social media-based health education interventions may conduct focus groups with college students at the study University prior to drafting health education materials to ensure the unique barriers

perceived by students at a given institution are highlighted. These focus groups could also be used to gather information on what outcomes are most relevant to this population as it pertains to increased participation in proper physical activity and dietary behaviors to be used in targeting improved outcome expectancy. It is noteworthy, however, that both groups in the current study already had moderately high outcome expectancy (combined mean: 9.7; scale range: 0 – 12 with higher scores better) and relatively low perceived barriers (combined mean: 28.6; scale range: 14 – 56 with lower scores better) at baseline—suggesting a ceiling effect may have been present for both groups on these outcomes.

The notable improvements observed among both groups over time for intrinsic motivation—a Self-Determination Theory-related outcome—was also positive. Increased intrinsic motivation has been associated with greater willingness to persist in proper physical activity and dietary behaviors among adults (Silva et al., 2010) and, more specifically, college students (Farmanbar et al., 2013; Phillips et al., 2016). Explanations for the increased intrinsic motivation observed among both groups may be attributable to the following three factors—some of which related to a degree to the improvements in Social Cognitive Theory-related constructs reviewed above: (a) participants perceived themselves to have increased *competence* for participating in proper health behaviors given the knowledge gained regarding proper physical activity and dietary behaviors via the health education posts made to each group’s Facebook page—an increase which may have promoted continued improvements in self-efficacy as well; (b) stemming from the greater social support reported by both groups, participants may have felt a greater

relatedness to other participants also trying to increase their participation in physical activity and nutritious eating behaviors more conducive to improved health; and (c) resulting from the potentially increased competency facilitated by greater knowledge of how to participate in proper physical activity and dietary behaviors and the observed increased self-efficacy for these health behaviors, participants may have perceived greater *self-determination/autonomy* for these behaviors. As Ryan and Deci (2000) posit, increasing an individual's perceived competence, relatedness, and self-determination is key in progressing an individual from certain degrees of amotivation and externally-regulated forms of extrinsic motivation to greater levels of internally-regulated forms of extrinsic motivation and intrinsic motivation. Of note, the fact self-efficacy and social support may have contributed to the increased intrinsic motivation observed has been supported in the literature. Briefly, Marr and Wilcox (2015) indicated that self-efficacy *and* social support mediate the relationship between college students' locus of control and physical activity/dietary behaviors. In discussing their observations, Marr and associates' suggested that promoting increased self-efficacy and social support might also improve intrinsic motivation for health behaviors as an individual moves from perceiving external loci of control as dictating health behavior participation (e.g., participating in proper health behaviors to "look good" or to "not feel guilty") to a more internal locus of control (e.g., participating in proper health behaviors because it makes the individual "feel good" and because an individual values being healthy). Therefore, based on the current study's observations and that of previous literature, it is suggested that continued focus needs to be placed on promoting college students' self-efficacy for health behaviors—preferably

using health education delivered via a medium wherein social support can also be promoted in a manner well-integrated into the daily lives of college students (e.g., social media).

A final and novel aspect of this health behavior change intervention was the inclusion of a nutrition education component. Observations indicated little change among dietary variables over time—contrary to the changes hypothesized in this study’s fourth hypothesis for study aim one. Indeed, while small decreases in overall kcaloric consumption were observed for both groups from baseline to 12 weeks, these findings may be more reflective of reduced participant motivation to report all food consumed each day on the ASA24 food recall than an actual decrease in kcaloric consumption. Further, overall observations for dietary outcomes were discouraging. For example, although an interaction effect was observed for sugar-sweetened beverage consumption amount over time accompanied, predictably, by an interaction effect for sugar-sweetened beverage consumption kcalories, this trend was not in the expected direction. In detail, while both groups demonstrated similar values for these outcomes at baseline, the experimental group demonstrated large increases in sugar-sweetened beverage consumption amount and kcalories at six weeks versus comparison before decreasing again at 12 weeks to levels observed at baseline. This contrasts the relatively stable values for these outcomes among the comparison group. Further, while trends toward significant interactions for vegetable consumption including and excluding legumes was observed, both groups concluded the intervention with intake levels equal to or below that observed at baseline and still well below the 3-cup national recommendation for

vegetable consumption (USDA, 2015).

These largely null and/or inconsistent trends in dietary outcomes are disheartening as college students have been observed to consume less than the recommended amount of fruit, vegetables, and whole grains while also having a high frequency sugar-sweetened beverage intake (Larson et al., 2010; Racette et al., 2005; USDA, 2015). Together, these behaviors can contribute to a positive kcaloric balance and weight gain during the college years (Levitsky et al., 2004). Observations regarding dietary outcomes are also surprising as prior research has indicated web-based nutrition education programs are capable of promoting improved self-regulation of proper dietary behaviors among college students (Marr & Wilcox, 2015; Poddar, Hosig, Anderson, Nickols-Richardson, & Duncan, 2010)—particularly those interventions which seek to improve self-efficacy for making proper dietary choices as was one objective during the current intervention. As the consumption of fruit, vegetables, and whole grains have been associated with reduced risk of non-communicable diseases like type 2 diabetes, heart disease, and some cancers (USDA, 2015), these observations deserve greater discussion.

In examining the literature on health behavior change interventions endeavoring to promote improved dietary behaviors, at least two factors might have contributed to small magnitudes of change observed for this study's dietary outcomes. First, health literacy might have played a role in the observations made. Indeed, research has indicated the importance of health literacy via appropriate health education in the promotion of long-term health behaviors (Nielsen-Bohlman et al., 2004; Rikard et al., 2016). Specific to college students' dietary behaviors, a recent investigation by Cha et al. (2014) observed

significant differences in dietary quality between individuals of low and high health literacy wherein individuals of low health literacy had poorer diets versus those of high health literacy. As alluded to above, it is noteworthy that Cha and colleagues found this difference to be related to self-efficacy for making healthy dietary choices and the ability to read/understand food labels. Therefore, while the current study did provide easy-to-implement nutrition education to participants, with some reference made regarding how to read food labels for discernment of lower fat options and foods made with whole grains, the preceding findings suggest more in-depth nutrition education might be needed in future studies. As mentioned previously, future studies designed similarly to the current investigation might experiment with the posting of easy-to-prepare/low-cost healthy meal recipes. These postings might also be accompanied by once-weekly links to articles/tutorials which review in lay terms (but in sufficient detail) the skills necessary to be an informed food consumer (e.g., how to read nutritional labels/food ingredient lists, where the healthiest foods are likely to be located within the supermarket). Second, and relatedly, it is important to take into consideration cues and priming for nutritious eating behaviors.

Cues refer to factors within an individual's environment which predispose the individual to engage in certain behaviors—regardless of whether this behavior is conducive to good health (Orbell & Verplanken, 2010). For example, the obesogenic environment within which we live (e.g., omnipresent advertisements for energy-dense, nutrient deficient food) has been observed to override individuals' conscious desire to consume healthier foods (Papies, Stroebe, & Aarts, 2008). Thus, to promote more

nutritious eating behaviors, researchers have developed interventions which seek to manipulate environmental cues and prime individuals for participation in healthier eating behaviors (Ohtomo, 2017; Papies, 2016). While extreme in methodology, Ohtomo (2017) observed that female college students exposed once to a picture of a slim female model engaged in less unhealthy snacking behaviors two weeks later compared to control. In the current study, participants were exposed to 12 empirically-based nutrition education tips (i.e., one tip per week). Yet, while these tips were empirically-derived, it might be that the claims made in these health education tips were not “radical” enough to override the unhealthy eating cues in the study participants’ environments given the fact college students often live near “all-you-can-eat” dining halls and fast-food establishments, with an additional concern being the lower cost of many less nutritious foods (Levitsky et al., 2004; Racette et al., 2005). Adding further corroboration to this reasoning is research stating multiple approaches are likely needed within health behavior change interventions to promote long-term sustainable changes to health behaviors (Lyons et al., 2014)—particularly health behaviors like diet which are more complex and less well understood by most individuals compared to physical activity. This adds further credibility to the recommendation that future health behavior change interventions of similar design to the current study develop/implement more comprehensive nutrition education materials.

An aspect of the current investigation also deserving of brief mention is the intervention use/acceptability observations as these data provide further context to study outcomes. Briefly, adherence to the theoretically-grounded, Facebook-delivered health education intervention was high, with adherence rates similar between groups at

approximately 87%. The health education tips provided were also received favorably as most participants found these tips to be “somewhat helpful” to “helpful” and implemented the tips between “two times per month” and “one to three times weekly”. As intervention adherence has been cited as important to overall intervention effectiveness (Matthews et al., 2012), the high adherence to the identical Facebook-delivered health education intervention piece available to both groups on their respective Facebook pages may have contributed to the positive study observations. Moreover, while modest, the slightly higher moderate-to-vigorous physical activity observed among experimental group participants may have been related to provision of the Polar M400 smartwatch to this group.

Experimental group participants found the smartwatch to be “somewhat easy” to operate while also perceiving the device to be “somewhat helpful” in assisting in the self-regulation of physical activity behaviors. Three aspects of the watch particularly enjoyed by experimental group participants of which might have also contributed to the slightly greater increases in moderate-to-vigorous physical activity observed among this group were: (a) the “exercise bar” on the smartwatch’s main screen that “filled up” as the individual accumulated more activity toward their daily goal; (b) the inactivity reminder which caused the watch to vibrate after 45 minutes of inactivity had been detected; and (c) the diary function that allowed the individual to examine all physical activity and energy expenditure data for each day of the past month. These features are noteworthy as smartwatches with built-in motivational aspects have been associated with increased intention to use these devices and improved device satisfaction among adults (Rupp et al.,

2018) and adolescents (Ridgers et al., 2018). Moreover, in use/acceptability analyses performed by Rote (2017) it was also observed that college students valued the motivational features of the study's Fitbit device as it pertained to assisting them to engage in greater amounts of physical activity behavior. Yet, the fact the experimental group did not exhibit greater improvements for any outcome versus the comparison group and, further, experienced decreased moderate-to-vigorous physical activity from the sixth to 12th week akin to the comparison group, may not have been entirely unexpected based upon prior literature.

Lyons et al. (2014) indicated that wearable technology devices and their associated smartphone applications possess few of the behavior change techniques which could be employed to assist in behavior change. Specifically, these researchers coded for the use of 93 different behavior change techniques employed on 13 popular commercially-available wearable technology devices (eight of which were smartwatches and/or wrist-worn devices). In detail, Lyons and colleagues observed a range of five to 14 behavior change techniques were employed (i.e., 5.4% - 15% of the available techniques) by these 13 devices and their associated smartphone applications. Therefore, given the fact the only difference between groups in the current study was the provision of the Polar M400 smartwatch to the experimental group, it might have been unrealistic to expect greater improvements among the outcomes assessed in this group versus the comparison group. As will be highlighted in the study limitations, perhaps a delayed-intervention control group would be prudent in a future investigation employing the current study's design.

Overall, the observations regarding the effectiveness of this combined smartwatch-

and social media-based health education intervention have real-world implications. As mentioned, researchers have posited the idea of “systems medicine”, an approach to medical treatment which leverages technology (e.g., smartphone applications, wearable technology) and big data analysis to provide more personalized and accessible healthcare and health promotion options to patients/clients from diverse populations/geographic areas (Hood et al., 2012). Within this systems medicine approach is the P4 Medicine framework (Flores et al., 2013) which states that the use of technology and big data analysis could facilitate the provision of healthcare that is: (a) Predictive – use of novel technology (e.g., wearable technology devices like smartwatches) may allow assessment of patient/client health behaviors and correlation with various health indices (e.g., biomarkers associated with cardiovascular disease)—facilitating initial prediction of future disease risk; (b) Preventive – greater predictive ability for a patient’s/client’s disease risk may facilitate development of health behavior change programs which endeavor to attenuate/reduce the disease risk(s) of the patient/client; (c) Personalized – the ability to gather information on individual-level health behaviors and indices allows for greater personalization of health behavior change programs to the patient/client—perhaps increasing adherence to the health behavior change program as suggested in recent literature (Schembre et al., 2018); and (4) Participatory – wellness teams can use the information gathered from technology such as smartwatches to educate patients/clients on more effectively managing their diseases/conditions independently—potentially using a secure social media-like, internet-based platform to further assist with educating patients/clients on health behavior changes congruent with limiting the future

development/current effects of certain diseases/conditions. Indeed, this approach mirrors the current paradigm shift within healthcare from a system that is reactive to a system which is proactive/preventive, with the integration of smartwatch and social media within healthcare posited for these purposes in prior literature (Lobelo et al., 2016; Welch et al., 2018; West, 2012).

Given the current study's positive observations, it might be possible to implement this type of healthcare platform. While slightly greater improvements for moderate-to-vigorous physical activity were observed among the experimental group receiving the combined smartwatch-based and theoretically-grounded, social media-delivered health education intervention, the fact both groups demonstrated similar improvements for several outcomes suggests that either approach used in this study may be feasible for improving health outcomes among college students and other populations within a systems medicine framework. Indeed, as the current study's approach to health behavior change was low-burden and well-integrated, this platform could be scaled and adapted to meet the needs of any organization and said organizations' patient/client base. Research (Kvedar, 2015; West, 2012) has highlighted the potential effect the combined use of modern technology like wearable technology, smartphone applications, and/or social media might have on community healthcare/health promotion—particularly when endeavoring to provide health-related access and resources to those living in more rural areas and/or of lower socioeconomic status. Of note, while these researchers possess a positive outlook on these technologies' healthcare/health promotion integration, it was stated that organizations will need to put in place a technological infrastructure which can

support this approach, with an additional consideration being individuals' health data privacy and willingness to share private health data which may be collected by devices like smartwatches. It is also noteworthy this approach to health behavior change necessitates valid, precise, and reliable smartwatch health metric data, with little measurement bias—factors of paramount importance if attempting to use wearable technology devices like smartwatches in a clinical setting during the development of personalized wellness programs. This topic is discussed in the second subsection of this Discussion below.

Discussion for Study Aim #2: Validity, Precision/Bias, and Reliability of Polar M400 Smartwatch

This study's second purpose was to evaluate the validity, precision/bias, and reliability of the Polar M400 smartwatch's measurement of daily activity time and steps per day via comparison of these health metric data to identical data provided by the research-grade ActiGraph Link accelerometer—an analysis facilitated by having experimental group participants wear both devices concurrently at the six and 12th week time points. Observations suggested the Polar M400 to have moderate validity and reliability but to demonstrate some bias and imprecision when assessing steps per day—particularly when individuals accrued lower steps per day. Observations were not as promising for the Polar M400's daily activity time measurements, with this measurement found invalid and unreliable despite little measurement bias and moderate precision for this metric's measurement.

Observations of higher validity and reliability for the Polar M400's steps per day

measurements is congruent with current literature and the hypothesis for the study's second aim. A previous review on the validity and reliability of smartwatch technology in physical activity assessment revealed high validity for step counts when assessed in laboratory-based settings and moderate validity for assessment of this metric in free-living settings (Evenson et al., 2015). Moreover, a recent review by Bunn et al. (2018) also corroborated the current study's observation that at lower mean steps per day, wrist-worn wearable technology (e.g., smartwatches, fitness bands) more greatly underestimated this metric than at higher mean steps per day. Compared to similar empirical studies, the present study also demonstrated congruence for validity in steps per day measurements. Ferguson et al. (2015) investigated the validity of several smartwatches and wearable fitness bands (Misfit Shine, Nike Fuel Band, Withings Pulse, Jawbone UP, Fitbit One, and Fitbit Zip), observing high-moderate to strong validity for step tracking compared to the research-grade ActiGraph GT3X+ (all $r > 0.80$)—observations aligned with those of Diaz et al. (2015) wherein researchers also observed high-moderate to strong validity for the step tracking of wrist-worn Fitbit Flex within a laboratory-based setting versus manually-counted steps (r range: 0.77 – 0.85). In another validation study of 10 popular smartwatches and wearable fitness bands (Apple Watch Sport, Pebble Smartwatch, Polar Loop, Garmin Vivosmart, Samsung Gear S, Misfit Flash, Jawbone Up Move, Flyfit, Moves, and Fitbit Charge HR), Fokkema and colleagues (2017) observed higher validity for step tracking at average and vigorous walking speeds (4.8 and 6.4 kilometers per hour, respectively) than during slow walking (3.2 kilometers per hour). Specifically, these researchers observed that while steps were

typically underestimated, the largest underestimations were seen at slower walking speed sessions during which fewer steps were taken—observations, again, similar to the current study’s observation that lower mean steps per day was associated with greater underestimation of this metric. It is noteworthy, however, that few studies have included any type of reliability measurement.

Diaz and colleagues (2015) did observe strong inter-device reliability (r : 0.99) of the Fitbit Flex’s step measurements when worn on different wrists but did not measure the test-retest reliability of these measurements during repeated walking trials. In fact, only one known study has investigated test-retest reliability of smartwatches in the assessment of steps. Specifically, the aforementioned study by Fokkema et al. (2017) found a wide range of test-retest reliability (r range: -0.02 – 0.97) when assessing 10 devices (listed above) step measurements across multiple trials of treadmill walking. Given the methodological differences between the current study and the study by Fokkema and colleagues, direct comparison is difficult. However, it is notable that during the 30-minute walking sessions performed during these researchers’ study, broad limits of agreement of up to $\pm 1,298$ steps were observed. These limits of agreement are smaller than that observed during the current study for steps per day. Yet, it should be kept in mind that the current study was: (a) conducted in a free-living setting; and (b) evaluated all steps taken *throughout the day* as opposed to only a *finite amount of time* during a laboratory-based physical activity session. These factors may have contributed to the larger limits of agreement for steps per day in the present investigation versus Fokkema et al. (2017), but still represent strengths of the current study given the need for more

research on smartwatch validity and reliability in free-living settings (Evenson et al., 2015). Given this study's observations of moderate test-retest reliability and validity for steps per day, use of the Polar M400 in the reasonably accurate assessment of steps per day over time may be permissible—particularly among healthy individuals engaging in higher mean steps per day during which less measurement bias is likely. Nonetheless, it is suggested that future studies pay stricter attention to the investigation of smartwatch reliability—evaluations which might increase the promise of using these devices in the long-term examination of various health metrics within community- and clinically-based settings as suggested by recent research (Henriksen et al., 2018; Schembre et al., 2018).

This study's observations regarding the validity, precision/bias, and reliability of the Polar M400's daily activity time measurements were not aligned with the hypothesis of the study's second aim but demonstrated some congruence with the limited validation research assessing smartwatch validity and reliability in the assessment of activity durations. In detail, in the aforementioned study by Ferguson and colleagues (2015), researchers observed a wide range of validity coefficients for the assessment of physical activity duration by several smartwatches (listed above) versus the criterion ActiGraph GT3x accelerometer (r range: 0.52 – 0.91)—similar to the r of 0.64 in the current study. Tully et al. (2014), however, observed higher validity (r : 0.86) when validating the Fitbit Zip's physical activity duration measurements than observed in the present investigation. Yet, these studies represent the only two known empirical investigations which sought to validate smartwatch activity time duration as most prior research in this emerging field have concerned validation of these devices' step, energy expenditure, heart rate, and

sleep measurements. Further, and perhaps unsurprisingly, no known study has conducted any type of reliability testing of smartwatch physical activity duration measurements—representing an area in need of future investigation.

While the current study did observe little measurement bias and moderate precision for the Polar M400's daily activity time duration measurements, the following two points are relevant. First, Bland-Altman plots assess how different mean values for a comparison device bias the differences between this device's measurements and a criterion device's measurements (Altman & Bland, 1983). Therefore, while the current study did not observe the Polar M400's measurement of high or low daily activity time measurements to possess measurement bias, this does not change the fact the device's daily activity time measurements were still inaccurate and often overestimated (as evidenced in the validity analyses). Second, and relatedly, while the coefficients of variation for the Polar M400 and ActiGraph Link's daily activity time measurements were quite similar at 16-17%, this metric is a measure of variability about the mean, not accuracy (Stokes, 1985). Stated simply, while both devices demonstrated similar dispersions around their respective mean daily activity time measurements, the fact remains that the Polar M400's measurement of this metric was inaccurate versus the criterion ActiGraph Link (again, see validity analyses). Given the poor validity and reliability of the Polar M400's daily activity time duration measurements, it is suggested researchers work with smartwatch manufacturers to improve upon the cut points used to assess durations and intensities of physical activity. Failure to do so limits the future use of these devices in the accurate assessment of physical activity behaviors and subsequent

development of health and wellness programs aligned with these devices' data (more on this matter below).

The current study expands upon this small literature base given its validation of a previously unresearched smartwatch, the Polar M400, during free-living conditions, with the most comprehensive validation statistics known to date. Notably, these observations have real-world implications as it pertains to the use of the Polar M400 in the intervention and subsequent promotion of improved health outcomes at the population-level and among health professional's clients/patients—implications which expand upon that discussed at the end of the discussion of the study's first aim (i.e., the effectiveness trial). Broadly, millions of consumers are purchasing and expecting to use smartwatches and the health metrics provided by these devices to self-regulate health behaviors (e.g., physical activity and dietary behaviors [indirectly via energy expenditure tracking]) in a manner conducive to improved health. Consumers, however, purchase smartwatches and other wearable technology under the assumption that these devices' health metric data can be trusted. In fact, in a recent study by Rupp et al. (2018), the researchers examined how personality traits impacted individuals' perception of wearable technology data trustworthiness, usability, and motivational impact. Researchers observed that while consumers' technology-related self-efficacy and physical activity levels had indirect positive associations with these individuals' desire to use wearable technology to improve fitness, whether the device's data output could be trusted and if the device had adequate motivational features demonstrated direct and significant associations with intention to use wearable technology. Thus, consumers may not be as willing to purchase

a device like the Polar M400 if only a select portion of the health metrics provided are valid and reliable. Further, when accounting for some of the comments made by the experimental group regarding the negative features of the Polar M400 (e.g., bulky, not as intuitive to use as other smartwatches, needs built-in heart rate monitor), marketing this smartwatch becomes increasingly difficult despite the advantage this smartwatch has in GPS functionality and a long battery life (~24 days when not using the GPS or heart rate tracking functions of the device).

The current study's observations are also relevant when examining how health professionals may utilize the information provided by smartwatches like the Polar M400. In discussing observations regarding the effectiveness of this study's intervention, the systems medicine approach and the P4 Medicine framework were reviewed (Flores et al., 2013; Hood et al., 2012). Briefly, it was mentioned how leveraging technology might allow for healthcare that is more proactive/preventive than reactive in addition to being *predictive* of disease/condition risk which—through *personalizing participatory* care for individual patients/clients—could possibly assist in *preventing* the individual from developing certain diseases/conditions. Yet, use of smartwatches in this manner would necessitate valid and reliable health metric data (i.e., highly accurate data over time). The present study's observations suggest that caution should be used if/when seeking to use the Polar M400 within healthcare programs/settings where highly accurate health metric information over time is needed. For example, if a health professional is using the Polar M400's daily activity time measurements to assist in setting daily physical activity duration goals for a physically inactive client, the program developed might be less

effective than it could be for outcomes such as weight loss given the Polar M400's overestimation of this health metric. Stated simply, the client may believe themselves to have met their physical activity duration goal on a given day when, in fact, the Polar M400 has inflated the client's physical activity duration. Although it is realized the mechanisms contributing to outcomes such as weight loss extend well beyond physical activity exclusively, physical activity remains an important and modifiable component of energy balance across time. Therefore, it can be seen how overestimation of daily activity time—particularly among clients/patients who will seek to participate in *just enough* physical activity to meet goals set with the help of a health professional—might reduce the long-term effectiveness of a program.

Companies producing smartwatches and/or fitness bands use proprietary algorithms within their devices to calculate health metrics like daily activity time, steps per day, energy expenditure, and heart rate, among other metrics like sleep duration and quality. Due to these differences, improving the accuracy over time for wearable technology health metric measurements presents a challenging task—particularly if seeking to ensure all companies produce devices with approximately the same long-term accuracy. Thus, it is suggested that researchers endeavor to build relationships with companies like Polar to develop validation studies and test various smartwatch algorithms' capability to accurately measure select health metrics versus “gold standard” assessments. For example, researchers could first set up laboratory-based simulations of activities commonly observed in free-living settings. Next, researchers could ask a company like Polar to provide several units of the same smartwatch—each with slightly different

algorithms for a health metric(s) like steps per day. During the study, the researchers could ask participants to engage in repeated trials of the simulated free-living activities wearing a different smartwatch unit each time to evaluate which unit had an algorithm most valid and reliable. Notably, if evaluating a health metric like steps per day, researchers could compare the steps registered by each smartwatch unit to the “gold standard” of manually-counted steps as done in other smartwatch validation research (Fokkema et al., 2017). Similar methodology could be employed if evaluating a health metric such as energy expenditure wherein comparisons could be made to energy expenditure measurements made with a portable metabolic analyzer. Regardless, observations from studies of this type could be shared with companies like Polar to ensure the device unit possessing algorithms producing the most valid and reliable health metric data is marketed.

While company-researcher collaborations akin to that outlined above may seem far-fetched and potentially riddled with conflicts of interest, investigating manners by which to improve the accuracy of smartwatch health metric data is paramount to the proposed use of these devices in healthcare settings. More importantly, these collaborations are vital to assisting in the promotion of improved health at the population level. As such, perhaps a sufficient (and less drastic) first step in promoting smartwatch health metric data accuracy is the development of certain validity, precision/bias, and reliability criteria for devices which are to be used within healthcare settings. Use of these criterion would promote at least two outcomes: (a) the data collected on clients/patients using certain smartwatch devices would be more trustworthy and amenable to use in the development

of comprehensive health behavior change interventions/programs; and (b) the prospect of losing revenue due to the inaccuracy of their smartwatch(es) might act as the impetus for smartwatch companies to collaborate with researchers to ensure sufficient long-term accuracy of their smartwatch devices. Only time will tell if these types of criteria will be put in place.

Current Study's Strengths

The following represent this study's strengths: (a) randomized design; (b) use of theory to inform intervention development, implementation, and analysis; (c) intervention methodology which was low-burden and well-integrated into college students' lifestyles by combining the use of two technologies (i.e., smartwatches, social media); (d) concurrent concentration on physical activity and nutritious eating behavior health education; (e) the high retention rate; (f) the routine intervention fidelity procedures implemented; and (g) investigation of the validity, precision/bias, and reliability of the Polar M400 smartwatch—a class of devices popular among young adults—within a free-living setting. This study's strengths are noteworthy for at least three major reasons:

- (a) As discussed, smartwatches and other wearable technologies continue to be highlighted as possible technologies to be used in the development and implementation of a P4 Medicine framework within a systems medicine healthcare approach (Flores et al., 2013; Hood et al., 2012). This study provides initial evidence regarding the feasibility of implementing a combined smartwatch and social media-based health education intervention which is low-burden and well-integrated into participants' lives. Notably, the study's high retention rate

and favorable remarks from participants suggest the intervention methodology to be present enough to be helpful, but not overwhelming.

- (b) The examination of the Polar M400's validity, precision/bias, and reliability in a free-living setting is notable given the increased use of this technology in the development and implementation of health behavior change programs despite most smartwatches having only been sparingly validated (Henriksen et al., 2018). Undoubtedly, as consumers value trustworthy health metric data above almost all other smartwatch features (Rupp et al., 2018), continued investigation into the validity, precision/bias, and reliability of smartwatch health metric data is important to smartwatch manufacturers' bottom lines. Validation of smartwatch health metric data is of even greater importance when used by health professionals as inaccurate data can decrease the effectiveness of health programs developed using these data (see brief example provided in Discussion #2 above).
- (c) The current study suggested some features which might assist in increasing intervention effectiveness. Briefly, this study's extensive intervention fidelity measures helped ensure participants adhered to the intervention and could correctly carry out the intervention's tasks. Explicitly, the researcher contacted participants every third week of the study with reminders to continue monitoring the Facebook-delivered health education intervention, with additional encouragement to try and implement these tips as frequently as possible. In addition to the preceding message(s), experimental group participants were asked to continue using the Polar M400 and to contact the researcher should any

questions/concerns arise regarding the device. Further, both groups received a detailed tutorial of their respective Facebook pages and the ASA24 food recall procedures, with the experimental group also receiving a detailed tutorial of the Polar M400's functions and the device's manual. As it pertains to the study's periodic assessments, detailed tracking procedures were used to ensure participants completed the necessary evaluations—particularly as it related to the more burdensome need to complete three ASA24 food recalls at each time point. Not only did these intervention fidelity procedures result in few missing data, but these procedures also ensured that continued attention was given to the intervention. Non-research programs endeavoring to scale this study's methodology might benefit from the implementation of some or all intervention fidelity procedures employed during this study given that adherence is often positively associated with intervention effectiveness (Matthews et al., 2012).

Current Study's Limitations

Despite this study's strengths, limitations were present and necessary to acknowledge when interpreting study observations. These limitations included:

- (a) The current study was unblinded. While the researcher made every effort to conceal group allocation from participants, asking comparison participants to discontinue smartwatch use may have hinted to comparison group participants the group into which they had been randomized. Moreover, contamination between groups could have been problematic as all college students were from the same University and attending some of the same classes.

- (b) No true control group was present. The only difference between the experimental and comparison groups within the current study was the provision of a smartwatch to experimental group participants. As such, the differential effects of a smartwatch on self-regulation in the increase of physical activity and decrease sedentary behavior may have been blunted given the fact the comparison group was also receiving a form of intervention via their separate, but content-identical Facebook group. Relatedly, examination of the true effect of the Facebook health education intervention on dietary behaviors is likely not possible as both groups received identical information via their respective Facebook pages (i.e., the dietary portion of the intervention was identical for both groups). Future studies may consider a delayed-intervention control group instead of a comparison group. Nonetheless, a delayed-intervention control group was not possible given the logistical constraints imposed by the researcher's impending graduation, with a true control group perhaps considered unethical.
- (c) Academic year breaks and midterms/finals weeks may have biased some observations. The study University had 16-week semesters meaning students were recruited for the first 3 weeks of the semester, completed baseline screening/testing and randomization during the fourth week, and then engaged in the intervention throughout the remainder of the semester. As such, the six week and 12 week testing sessions often coincided with holiday breaks and midterms/finals—possibly biasing physical activity and dietary behaviors. Indeed, it might be that the lower physical activity observed at 12 weeks compared to six

weeks was partially resultant from the college student participants engaging in greater amounts of sedentary behavior as they studied for finals. Moreover, when examining sugar-sweetened beverage consumption, it is notable that an item frequently reported was “hot cocoa sweetened with sugar”—particularly as Christmas Break drew nearer (e.g., first wave participants) and during the early months of 2018 (e.g., second wave participants). Researchers conducting similar studies might want to experiment with recruitment periods prior to semester’s start—facilitating immediate intervention initiation at the beginning of the semester—to reduce the bias academic year breaks and finals may have on study outcome measurements.

- (d) The psychosocial questionnaires employed demonstrated an orientation toward physical activity rather than general health or dietary behaviors. Thus, caution is suggested in interpreting how college students’ diet-related Social Cognitive Theory- and Self-Determination Theory-related constructs changed due the intervention—representing an area of improvement for future studies. Nonetheless, numerous studies among college students referenced previously demonstrated how promoting constructs aligned with these theories—as done via the theoretically-grounded, Facebook-delivered health education intervention during the current study—can increase participation in both physical activity and dietary behaviors (Marr & Wilcox, 2015; Mirzaei-Alavijeh et al., 2018; Von Ah et al., 2004).

- (e) No exercise or dietary programs were explicitly provided. While the purpose of

the invention was to provide low-burden and well-integrated physical activity and dietary intervention for college students, it is recognized that the Facebook platform could have also been used to provide the participants with easy-to-implement exercise and dietary programs in addition to health education articles and tutorials. Additional investigations may examine the feasibility of including and distributing this content via social media.

- (f) Social Cognitive Theory- and Self-Determination Theory-related behavioral techniques could be implemented to a stronger degree within future interventions. Specifically, while the current study drafted all health education tips based upon these theories' constituent constructs, the health education tips might have been perceived as mostly informational in nature. Future studies may use the unique features of social media platforms like Facebook to, for instance, develop polls which quiz participants on their understanding of the content posted, with an additional request for participants to post a brief explanation of how they might implement a given health education tip in their own life. Other ideas for deeper integration of behavioral theory within this type of intervention might also include asking participants to set physical activity- and nutrition-related goals and/or make weekly posts to their respective Facebook group pertaining to the obstacles they faced in making proper physical activity and dietary choices. Not only would this allow greater internalization of the health education tips by participants, but it would also facilitate the ability of researchers and health professionals to make modifications to the intervention to best meet the unique needs of participants

while allowing participants to support one another as they face these obstacles.

- (g) The small sample size limited the study's power and allowed only for the determination of large effect. Specifically, to detect a 4-minute group difference in mean daily moderate-to-vigorous physical activity duration, a power analysis stated the need for 45 participants per group. Relatedly, the study was conducted with healthy college students from a single University in the northern U.S. with a sample of predominantly female, Caucasian participants. This homogeneity limits the generalizability of the observations to this population. Therefore, future studies may seek to conduct multi-site interventions among other healthy and clinical populations to not only increase heterogeneity/generalizability, but also to increase study sample size and associated statistical power.

Chapter Six: Conclusion

Observations of the current study indicated that an intervention combining the use of a smartwatch and theoretically-grounded, social media-delivered health education intervention may not provide much greater benefit than a standalone theoretically-grounded, social media-delivered health education intervention on college students' health outcomes. Nevertheless, the improvements observed for moderate-to-vigorous physical activity, weight, and psychosocial constructs within both groups are promising. Specifically, the fact the low-burden, well-integrated approach to improving college student health outcomes employed in both groups was successful suggests this model could be scaled for use on bigger platforms among more diverse populations. Notably, however, even greater concentration should be placed on nutrition education to produce greater beneficial changes in dietary behaviors than observed in the current study—perhaps using meal plans and nutrition-related articles and educational tutorials delivered via social media to do so. Finally, validation of the Polar M400 versus the ActiGraph Link suggested the smartwatch to have moderate validity and reliability for steps per day, with poor validity and reliability observed for this device's daily activity time measurements. Thus, while use of the Polar M400 in steps per day tracking over time may be permissible among healthy populations accruing larger amounts of steps per day, caution is suggested if using the Polar M400's health metric information is being used to develop health behavior change programs wherein highly accurate health metric instrumentation/measurements are vital (e.g., clinical weight loss programs).

Future studies should include a larger and more heterogenous sample, discern a

way by which to limit the confounding effect of academic school year breaks (e.g., Thanksgiving/Christmas breaks, spring break, and summer break) and midterms/finals on intervention outcomes, and consider including a delayed-intervention control.

Chapter Seven: Bibliography

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[helsinki-ethical-principles-for-medical-research-involving-human-subjects/](https://www.wma.net/policies-post/wma-declaration-of-helsinki-ethical-principles-for-medical-research-involving-human-subjects/).

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Chapter Eight: Appendices

Appendix A. CONSORT Checklist

CONSORT 2010 checklist of information to include when reporting a randomised trial*

Section/Topic	Item No	Checklist item	Report ed on page No.
Title and abstract			
	1a	Identification as a randomised trial in the title	Page i
	1b	Structured summary of trial design, methods, results, and conclusions (for specific guidance see CONSORT for abstracts)	Pages vi - xii
Introduction			
Background and objectives	2a	Scientific background and explanation of rationale	Pages 1 - 7; 11 - 41
	2b	Specific objectives or hypotheses	Page 7-9
Methods			
Trial design	3a	Description of trial design (such as parallel, factorial) including allocation ratio	Pages 44 - 45
	3b	Important changes to methods after trial commencement (such as eligibility criteria), with reasons	N/A
Participants	4a	Eligibility criteria for participants	Pages 42 - 43

	4b	Settings and locations where the data were collected	Pages 42; 54 - 60
Interventions	5	The interventions for each group with sufficient details to allow replication, including how and when they were actually administered	Pages 54 - 60
Outcomes	6a	Completely defined pre-specified primary and secondary outcome measures, including how and when they were assessed	Pages 45 - 54
	6b	Any changes to trial outcomes after the trial commenced, with reasons	N/A
Sample size	7a	How sample size was determined	Pages 42 - 43
	7b	When applicable, explanation of any interim analyses and stopping guidelines	N/A
Randomisation:			
Sequence generation	8a	Method used to generate the random allocation sequence	Pages 44 - 45
	8b	Type of randomisation; details of any restriction (such as blocking and block size)	Pages 44 - 45
Allocation concealment mechanism	9	Mechanism used to implement the random allocation sequence (such as sequentially numbered containers), describing any steps taken to conceal the sequence until interventions were assigned	Pages 44 - 45
Implementation	10	Who generated the random allocation sequence, who enrolled participants, and who assigned participants to interventions	Pages 44 - 45
Blinding	11a	If done, who was blinded after assignment to interventions (for example, participants, care providers, those assessing outcomes) and how	N/A
	11b	If relevant, description of the similarity of interventions	Pages 45 - 54
Statistical methods	12a	Statistical methods used to compare groups for primary and secondary outcomes	Pages 60 - 64
	12b	Methods for additional analyses, such as subgroup analyses and adjusted analyses	Pages 60 - 64
Results			
Participant flow (a diagram is strongly recommended)	13a	For each group, the numbers of participants who were randomly assigned, received intended treatment, and were analysed for the primary outcome	Pages 65 - 67
	13b	For each group, losses and exclusions after randomisation, together with reasons	Pages 65 - 67

Recruitment	14a	Dates defining the periods of recruitment and follow-up	N/A
	14b	Why the trial ended or was stopped	N/A
Baseline data	15	A table showing baseline demographic and clinical characteristics for each group	Pages 68 - 71
Numbers analysed	16	For each group, number of participants (denominator) included in each analysis and whether the analysis was by original assigned groups	See CONSORT Flow Diagram (Figure 4-1); Pages 65 - 67
Outcomes and estimation	17a	For each primary and secondary outcome, results for each group, and the estimated effect size and its precision (such as 95% confidence interval)	Pages 71 - 86
	17b	For binary outcomes, presentation of both absolute and relative effect sizes is recommended	N/A
Ancillary analyses	18	Results of any other analyses performed, including subgroup analyses and adjusted analyses, distinguishing pre-specified from exploratory	N/A
Harms	19	All important harms or unintended effects in each group (for specific guidance see CONSORT for harms)	N/A
Discussion			
Limitations	20	Trial limitations, addressing sources of potential bias, imprecision, and, if relevant, multiplicity of analyses	Pages 127 - 130
Generalisability	21	Generalisability (external validity, applicability) of the trial findings	Pages 87 - 124
Interpretation	22	Interpretation consistent with results, balancing benefits and harms, and considering other relevant evidence	Pages 87 - 124
Other information			
Registration	23	Registration number and name of trial registry	Page 42
Protocol	24	Where the full trial protocol can be accessed, if available	Page 42
Funding	25	Sources of funding and other support (such as supply of drugs), role of funders	Not included given that this is a dissertation

*We strongly recommend reading this statement in conjunction with the CONSORT 2010 Explanation and Elaboration for important clarifications on all the items. If relevant, we also recommend reading CONSORT extensions for cluster randomised trials, non-inferiority and equivalence trials, non-pharmacological treatments, herbal interventions, and pragmatic trials. Additional extensions are forthcoming: for those and for up to date references relevant to this checklist, see www.consort-statement.org.

Appendix B. IRB Approval Form

UNIVERSITY OF MINNESOTA

Twin Cities Campus

Human Research Protection Program
Office of the Vice President for Research

1528 Mayo Memorial Building
420 Delaware Street S.E.
MLR, 620
Minneapolis, MN 55455
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APPROVAL OF NEW STUDY

June 19, 2017

Zan Gao

612-626-4639
gaoz@umn.edu

Dear Zan Gao:

On 6/16/2017, the IRB reviewed the following submission:

Type of Review:	Initial Study
Title of Study:	Use of Health Wearables to Improve Physical Activity and Eating Behaviors among College Students: A 12-week Randomized Pilot Study
Investigator:	Zan Gao
IRB ID:	STUDY00000386
Sponsored Funding:	None
Grant ID/Con Number:	None
Internal UMN Funding:	None
Fund Management Outside University:	None
IND, IDE, or HDE:	None
Documents Reviewed with this Submission:	<ul style="list-style-type: none"> • Recruitment Speech-Effectiveness of Health Wearable on College Student Health.pdf, Category: Recruitment Materials; • BioMed Template-Effectiveness of Health Wearables on College Student Health.pdf, Category: IRB Protocol; • Appendix A-BiWeekly Tips for Polar M400 Study.pdf, Category: Other; • Recruitment Email-Effectiveness of Health Wearable on College Student Health.pdf, Category: Recruitment Materials; • Recruitment Flyer-Effectiveness of Health

Driven to Discover™

We value feedback from the research community and would like to hear about your experience. The link below will take you to a brief survey that will take a minute or two to complete. The questions are basic, but your responses will help us better understand what we are doing well and areas that may require improvement. Thank you in advance for completing the survey.

Even if you have provided feedback in the past, we want and welcome your evaluation.

https://umn.qualtrics.com/SE/?SID=SV_5BiYrqPNMJRQSBu

Appendix C. Informed Consent

EFFECTIVENESS OF HEALTH WEARABLE ON COLLEGE STUDENT HEALTH: CONSENT TO BE A RESEARCH PARTICIPANT UNIVERSITY OF MINNESOTA

A. BACKGROUND AND PURPOSE

College students are at risk for increased rates of overweight and obesity due to the increased responsibilities of living independently and managing school, jobs, and social lives. Further, some college students are also making physical activity- and nutrition-related decisions on their own for the first time. The preceding factors have led to moderately-high levels of overweight and obesity among college students, with approximately half of college students reporting complete physical inactivity and fried-/fast-food consumption at least 3 times weekly. Fortunately, college students represent a large proportion of the approximately \$5 billion health wearable market (e.g., smartwatches) and comprise a majority of users on Facebook—technologies/platforms which might be used to help college students improve their health. Therefore, the combined use of health wearable technology, these devices' associated smartphone applications, and a social media-delivered health intervention, may prove appealing and effective as a health promotion strategy among college students.

The current study will evaluate the effectiveness of the Polar M400 Smartwatch, used in combination with a twice-weekly Facebook-delivered health intervention, in the promotion of more healthful physical activity and nutritious eating behaviors over 12 weeks among college students. Moreover, the study will evaluate the accuracy of the Polar M400 in the assessment of physical activity and energy expenditure. Throughout the duration of this intervention, changes in participants' physical activity, body composition, cardiorespiratory fitness, psychological health, and nutritious eating behaviors will be assessed. Additionally, it is also believed that the Polar M400 will be proven accurate in the assessment of college students' physical activity behaviors.

B. PROCEDURES

Participant requirements:

- 18-35 years old with body mass index ≥ 18.5
- Currently engaged in < 150 minutes/week of physical activity
- Currently eating < 2 servings of fruit and < 3 servings of vegetables daily
- No diagnosed physical/mental disability
- Is willing to be randomized into either an intervention or comparison group, provides informed consent, and completes the Physical Activity Readiness Questionnaire

Potential participants who do not meet one or more of the above requirements will be excluded from participation in the current study. No participant, however, will be excluded on the basis of gender or race/ethnicity.

Procedures:

Participants will be randomized into two groups following screening against the aforementioned participant requirements:

- Intervention group: Participants will be provided a Polar M400 to track physical activity and energy expenditure while also being included in a private Facebook group wherein Social Cognitive Theory-based physical activity and nutritious eating tips will be provided twice weekly for 12 weeks.
- Comparison Group: Participants will be included exclusively in a separate, but content-identical, private Facebook group for 12 weeks.

The study will be 12 weeks in duration and will include the following testing for all participants at baseline, 6 weeks (mid-intervention), and 12 weeks (post-intervention):

- Baseline testing (Week 1)- *Duration of Lab Visit: 45 minutes*
 - *Anthropometric measurements:* Participant's height and weight measurements will be taken within the University of Minnesota's Physical Activity Epidemiology Laboratory.
 - *Questionnaires regarding social-cognitive beliefs and intrinsic motivation:* Questionnaires assessing the following physical activity-related social-cognitive beliefs will be administered: barriers, enjoyment, outcome expectancy, and self-efficacy. Additionally, intrinsic motivation will be evaluated. These questionnaires will be taken within the Physical Activity Epidemiology Laboratory.
 - *Cardiorespiratory fitness:* The 3-minute step test will be administered to each participant within the Physical Activity Epidemiology Laboratory.
 - *Body composition:* Private bioelectrical impedance testing will be administered to each participant within the Physical Activity Epidemiology Laboratory.
 - *Habitual physical activity levels:* Each participant will be assigned an accelerometer to wear for 7 days, collecting a minimum of three weekdays and two weekend days.
 - *Dietary behaviors:* Participants will be asked to complete National Cancer Institute's Automated Self-Administered 24-hour dietary recall will be administered online 3 times on random dates during the 7 days following baseline testing within the Physical Activity Epidemiology Laboratory.
- Mid-intervention testing (Week 6)- *Duration of Lab Visit: 10 minutes*
 - *Habitual physical activity levels:* Each participant will be assigned an accelerometer to wear for 7 days, collecting a minimum of three weekdays and two weekend days.
- Post-intervention testing (Week 12)- *Duration of Lab Visit: 45 minutes*
 - Participants will be administered the same sequence of tests as seen in the baseline (Week 1) testing above (i.e., assessment of habitual physical activity levels, cardiorespiratory fitness, body composition, anthropometric measurements, social cognitive beliefs, intrinsic motivation, and dietary behaviors).

C. RISKS/DISCOMFORTS

This study has the potential to increase your physical activity participation and, as a result, risks associated with increases in physical activity participation are possible. These risks include joint pain, muscle strains/sprains, swelling, weakness, dizziness, and fatigue. If you develop any of these conditions for greater than 1-2 hours after your

exercise session, it is recommended that you use ice, compression, and, if needed, seek the advice of a physician. Further some mental distress is possible as a result of body composition testing and the assessment of physical activity-related social-cognitive beliefs and intrinsic motivation—although, the risk of this mental distress is very low. Finally, some risk is involved in joining the study-related Facebook Groups as other participants will also be included within the Groups. This risk includes breach of privacy by other participants.

The *potential risks* of your participation in this study are:

- (1) Delayed onset muscle soreness occurring several hours to a couple of days after physical activity engagement.
- (2) Given the study's potential to increase your physical activity participation a possibility exists for the development of symptoms such as muscular strains/sprains, shortness of breath, joint pain, cramping, fatigue, fainting, and dizziness.
- (3) Lack of motivation to participate in physical activity due to potential muscle soreness/fatigue and/or frustration will progress toward health-related goals.
- (4) Although very unlikely, mental distress caused by the administration of bio-electrical impedance testing to discern body composition and the assessment of physical activity-related social cognitive beliefs and intrinsic motivation is possible.

Risk Management:

- (1) In order to minimize the risk of muscle strains and sprains during physical activity participation, the researcher will discuss with you the importance of a proper warm-up and cool-down.
- (2) Information on the proper care and treatment of delayed onset muscle soreness and joint pain will be reviewed.
- (3) A review of information related to discerning the proper intensity of exercise will be reviewed.
- (4) If the potential increase in physical activity participation which might result from your enrollment in this study causes too much pain or becomes too difficult, you have the opportunity to discontinue participation in the study at any point.
- (5) Mental distress resulting from the assessment of body composition and the assessment of physical activity-related social cognitive beliefs and intrinsic motivation will be minimized by conducting the bio-electric impedance body composition testing and psychological testing in a private environment with only the principal investigator present.
- (6) To ensure the privacy of the study-related Facebook Groups, the principal investigator will ensure: (1) that the Facebook Groups are “secret” on Facebook, meaning the Groups will not be searchable on the social media platform and “invitation only” (i.e., individuals cannot join the Groups unless invited by the principal investigator); and (2) that all participants conduct themselves properly within the Groups. The study-related Facebook Groups will be deleted upon the study's conclusion.

D. BENEFITS

The potential direct benefits following your participation in this research is weight loss and improvements in social cognitive beliefs (i.e., increased self-efficacy, outcome expectancy, social support and enjoyment as well as decreased barriers) and intrinsic motivation related to physical activity as well as participation in more nutritious eating behaviors. Further, the participants may also receive health-related benefits related to improved cardiorespiratory fitness and more favorable body composition (i.e., increases in lean mass and decreases in fat mass) resulting from the intervention. However, any improved health resulting from study participation will not be permanent, but dependent upon the participant's continued participation in physical activity and nutritious eating behaviors.

E. COSTS

There will be no costs to you as a result of taking part in this study other than the time spent participating. Notably, individuals included in the experimental group receiving the Polar M400 smartwatch will be held responsible if the device is lost, stolen, or damaged while in their possession.

F. COMPENSATION

Taking part in this study is completely voluntary. Completion of all study protocol will result in the receipt of up to \$30 in VISA gift cards good at any retailer. Specifically, you will receive \$10 for completion of each testing session (i.e., baseline testing as well as the 6 and 12 week testing sessions) in the form of a VISA gift card, with payments prorated based upon the number of testing sessions you successfully complete (e.g., if you only complete two testing sessions you will only receive \$20).

G. CONFIDENTIALITY

Confidentiality of data will be maintained by assigning you a unique participant code. All data will be labeled with this code and no references will be made to link you with your data. The participant code key will be kept in a locked file cabinet within the principal investigator's office. Data will be stored on the principal investigator's computer and one computer within the University of Minnesota's Physical Activity Epidemiology Laboratory. Both computers are password encrypted ensuring all access to files will only be possible by the principal investigator. Data will not be stored via any other methodology and will not be transported outside of the aforementioned locations.

H. QUESTIONS

If you have any questions or concerns about participation in this study, you should first talk with the principal investigator.

Zachary Pope, Ph.D. Candidate
Graduate Research Assistant: University of Minnesota
Room 310, Williamson Hall
231 Pillsbury Drive SE
Minneapolis, MN 55455
(208)-891-9421
popex157@umn.edu

If you have any questions or concerns regarding the study and would like to talk to someone other than the researcher(s), you are encouraged to contact the Research Subjects' Advocate Line, D-528 Mayo, 420 Delaware Street S.E., Minneapolis, Minnesota, 55455; telephone (612)-625-1650.

Should you feel any discomfort due to participation in this research, you should contact your healthcare provider.

I. CONSENT

You will be given a copy of this consent form to keep.

PARTICIPATION IN RESEARCH IS VOLUNTARY. You are encouraged to ask questions at any time and are free to decline to be in this study, or to withdraw from it at any point. Your decision as to whether or not to participate in this study will have no influence on your present or future status as a student, research participant, or employee at the University of Minnesota.

I give my consent to participate in this study:

_____	_____
Signature of Study Participant	Date

_____	_____
Signature of Person Obtaining Consent	Date

THE UNIVERSITY OF MINNESOTA INSTITUTIONAL REVIEW BOARD HAS REVIEWED THIS PROJECT FOR THE PROTECTION OF HUMAN PARTICIPANTS IN RESEARCH.

Appendix D. Physical Activity Readiness Questionnaire

Physical Activity Readiness
Questionnaire - PAR-Q
(revised 2002)

PAR-Q & YOU

(A Questionnaire for People Aged 15 to 69)

Regular physical activity is fun and healthy and increasingly more people are starting to become more active every day. Being more active is very safe for most people. However, some people should check with their doctor before they start becoming much more physically active.

If you are planning to become much more physically active than you are now, start by answering the seven questions in the box below. If you are between the ages of 15 and 69, the PAR-Q will tell you if you should check with your doctor before you start. If you are over 69 years of age, and you are not used to being very active, check with your doctor.

Common sense is your best guide when you answer these questions. Please read the questions carefully and answer each one honestly: check YES or NO.

YES	NO	
☐	☐	1. Has your doctor ever said that you have a heart condition <u>and</u> that you should only do physical activity recommended by a doctor?
☐	☐	2. Do you feel pain in your chest when you do physical activity?
☐	☐	3. In the past month, have you had chest pain when you were not doing physical activity?
☐	☐	4. Do you lose your balance because of dizziness or do you ever lose consciousness?
☐	☐	5. Do you have a bone or joint problem (for example, back, knee or hip) that could be made worse by a change in your physical activity?
☐	☐	6. Is your doctor currently prescribing drugs (for example, water pills) for your blood pressure or heart condition?
☐	☐	7. Do you know of <u>any other reason</u> why you should not do physical activity?

If
you
answered

YES to one or more questions

Talk with your doctor by phone or in person BEFORE you start becoming much more physically active or BEFORE you have a fitness appraisal. Tell your doctor about the PAR-Q and which questions you answered YES.

- You may be able to do any activity you want — as long as you start slowly and build up gradually. Or, you may need to restrict your activities to those which are safe for you. Talk with your doctor about the kinds of activities you wish to participate in and follow his/her advice.
- Find out which community programs are safe and helpful for you.

NO to all questions

If you answered NO honestly to all PAR-Q questions, you can be reasonably sure that you can:

- start becoming much more physically active — begin slowly and build up gradually. This is the safest and easiest way to go.
- take part in a fitness appraisal — this is an excellent way to determine your basic fitness so that you can plan the best way for you to live actively. It is also highly recommended that you have your blood pressure evaluated. If your reading is over 144/94, talk with your doctor before you start becoming much more physically active.

DELAY BECOMING MUCH MORE ACTIVE:

- if you are not feeling well because of a temporary illness such as a cold or a fever — wait until you feel better; or
- if you are or may be pregnant — talk to your doctor before you start becoming more active.

PLEASE NOTE: If your health changes so that you then answer YES to any of the above questions, tell your fitness or health professional. Ask whether you should change your physical activity plan.

Informed Use of the PAR-Q: The Canadian Society for Exercise Physiology, Health Canada, and their agents assume no liability for persons who undertake physical activity, and if in doubt after completing this questionnaire, consult your doctor prior to physical activity.

No changes permitted. You are encouraged to photocopy the PAR-Q but only if you use the entire form.

NOTE: If the PAR-Q is being given to a person before he or she participates in a physical activity program or a fitness appraisal, this section may be used for legal or administrative purposes.

"I have read, understood and completed this questionnaire. Any questions I had were answered to my full satisfaction."

NAME _____

SIGNATURE _____

DATE _____

SIGNATURE OF PARENT
or GUARDIAN (for participants under the age of majority) _____

WITNESS _____

Note: This physical activity clearance is valid for a maximum of 12 months from the date it is completed and becomes invalid if your condition changes so that you would answer YES to any of the seven questions.

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Appendix E. Physical Activity Screening Questionnaire

Physical Activity Screening Questionnaire

Participant Name: _____ **Date:** _____

Over the past month, did you participate in any moderate-intensity physical activity? What I mean by moderate-intensity activity is any activity that feels as hard or harder than a brisk walk. It gets your heart rate going faster and feels like you are running late for an appointment or walking to get out of the rain. For the activity to be counted, it needs to be for at least 10 continuous minutes without stopping. Some examples of activities that are at least of moderate intensity could include brisk walking 3-4 mph, running, aerobic dance, swimming, and bicycling.

YES NO

If no, then continue the survey to ascertain approximately how much physical activity the individual has engaged in, with the knowledge the individual is eligible for this criteria of the study.

If yes, please remember to clarify that it was at least 10 continuous minutes without stopping and was at least of moderate intensity. For example, someone might say they did 60 minutes of housework but only 30 of those minutes were at the moderate-intensity level and were at least 10 minutes at a time.

Regardless of whether the individual responded yes OR no, pose the following questions:

- a. What activities have you done over the past month?
- b. How many times per week (average)?
- c. For how many minutes each time (average)?
- d. How long have you been doing this activity (average)? (Note: Remind individual to be specific: weekly, monthly, yearly)

If greater than 90 minutes per week of at least moderate-intensity physical activity, then the individual is ineligible for the study.

If there is a question as to whether the activities are at the moderate-intensity level, please let the individual know that you will get back into touch with them. It is at this point you will contact Zach regarding the individual's responses.

3. Over the last month, how often did you eat **lettuce salad (with or without other vegetables)**?

- ☐ Never
(Go to Question 4)
 ☐ 1-3 times last month
 ☐ 1-2 times per week
 ☐ 3-4 times per week
 ☐ 5-6 times per week
 ☐ 1 time per day
 ☐ 2 times per day
 ☐ 3 times per day
 ☐ 4 times per day
 ☐ 5 or more times per day

3a. Each time you ate **lettuce salad**, how much did you usually eat?

- ☐ About ½ cup
 ☐ About 1 cup
 ☐ About 2 cups
 ☐ More than 2 cups

4. Over the last month, how often did you eat **French fries or fried potatoes**?

- ☐ Never
(Go to Question 5)
 ☐ 1-3 times last month
 ☐ 1-2 times per week
 ☐ 3-4 times per week
 ☐ 5-6 times per week
 ☐ 1 time per day
 ☐ 2 times per day
 ☐ 3 times per day
 ☐ 4 times per day
 ☐ 5 or more times per day

4a. Each time you ate **French fries or fried potatoes**, how much did you usually eat?

- ☐ Small order or less
(About 1 cup or less)
 ☐ Medium order
(About 1½ cups)
 ☐ Large order
(About 2 cups)
 ☐ Super Size order or more
(About 3 cups or more)

5. Over the last month, how often did you eat **other white potatoes**? Count **baked, boiled, and mashed potatoes, potato salad, and white potatoes that were not fried**.

- ☐ Never
(Go to Question 6)
 ☐ 1-3 times last month
 ☐ 1-2 times per week
 ☐ 3-4 times per week
 ☐ 5-6 times per week
 ☐ 1 time per day
 ☐ 2 times per day
 ☐ 3 times per day
 ☐ 4 times per day
 ☐ 5 or more times per day

5a. Each time you ate **these potatoes**, how much did you usually eat?

- ☐ 1 small potato or less
(½ cup or less)
 ☐ 1 medium potato
(½ to 1 cup)
 ☐ 1 large potato
(1 to 1½ cups)
 ☐ 2 medium potatoes or more
(1½ cups or more)

6. Over the last month, how often did you eat **cooked dried beans**? Count **baked beans, bean soup, refried beans, pork and beans and other bean dishes**.

- ☐ Never
(Go to Question 7)
 ☐ 1-3 times last month
 ☐ 1-2 times per week
 ☐ 3-4 times per week
 ☐ 5-6 times per week
 ☐ 1 time per day
 ☐ 2 times per day
 ☐ 3 times per day
 ☐ 4 times per day
 ☐ 5 or more times per day

6a. Each time you ate **these beans**, how much did you usually eat?

- ☐ Less than ½ cup
 ☐ ½ to 1 cup
 ☐ 1 to 1½ cups
 ☐ More than 1½ cups

7. Over the last month, how often did you eat **other vegetables**?

DO NOT COUNT:

- Lettuce salads
- White potatoes
- Cooked dried beans
- Vegetables in mixtures, such as in sandwiches, omelets, casseroles, Mexican dishes, stews, stir-fry, soups, etc.
- Rice

COUNT: • All other vegetables—raw, cooked, canned, and frozen

☐ Never
(Go to Question 8)
 ☐ 1-3 times last month
 ☐ 1-2 times per week
 ☐ 3-4 times per week
 ☐ 5-6 times per week
 ☐ 1 time per day
 ☐ 2 times per day
 ☐ 3 times per day
 ☐ 4 times per day
 ☐ 5 or more times per day

7a. Each of these times that you ate **other vegetables**, how much did you usually eat?

☐ Less than 1/4 cup
 ☐ 1/4 to 1 cup
 ☐ 1 to 2 cups
 ☐ More than 2 cups

8. Over the last month, how often did you eat **tomato sauce**? Include tomato sauce on pasta or macaroni, rice, pizza and other dishes.

☐ Never
(Go to Question 9)
 ☐ 1-3 times last month
 ☐ 1-2 times per week
 ☐ 3-4 times per week
 ☐ 5-6 times per week
 ☐ 1 time per day
 ☐ 2 times per day
 ☐ 3 times per day
 ☐ 4 times per day
 ☐ 5 or more times per day

8a. Each time you ate **tomato sauce**, how much did you usually eat?

☐ About 1/4 cup
 ☐ About 1/2 cup
 ☐ About 1 cup
 ☐ More than 1 cup

9. Over the last month, how often did you eat **vegetable soups**? Include tomato soup, gazpacho, beef with vegetable soup, minestrone soup, and other soups made with vegetables.

☐ Never
(Go to Question 10)
 ☐ 1-3 times last month
 ☐ 1-2 times per week
 ☐ 3-4 times per week
 ☐ 5-6 times per week
 ☐ 1 time per day
 ☐ 2 times per day
 ☐ 3 times per day
 ☐ 4 times per day
 ☐ 5 or more times per day

9a. Each time you ate **vegetable soup**, how much did you usually eat?

☐ Less than 1 cup
 ☐ 1 to 2 cups
 ☐ 2 to 3 cups
 ☐ More than 3 cups

10. Over the last month, how often did you eat **mixtures that included vegetables**? Count such foods as sandwiches, casseroles, stews, stir-fry, omelets, and tacos.

☐ Never
 ☐ 1-3 times last month
 ☐ 1-2 times per week
 ☐ 3-4 times per week
 ☐ 5-6 times per week
 ☐ 1 time per day
 ☐ 2 times per day
 ☐ 3 times per day
 ☐ 4 times per day
 ☐ 5 or more times per day

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Thank you very much for completing this questionnaire.
 Please return it in the enclosed, postage-paid envelope or to the
 address listed on the front page.

Appendix G. Psychosocial Outcomes/Anthropometric and Physiological Questionnaire.

For PAEL Use Only:

- Subject Code: _____
- Date of Assessment: _____

Health Behaviors Survey

This survey asks about thoughts, feelings, and behaviors you have regarding health behaviors.

Read each question carefully. Select your answer choice and fill in the circle completely. If you wish to change an answer, please completely erase the previous choice.

Your answers are completely confidential and will remain completely anonymous. Additionally, your answers are important to us. If you have any questions, please do not hesitate to ask a research assistant for help.

Demographic Information	
1. Gender:	
☐ Male	
☐ Female	
2. What is your date of birth? Month _____ Day _____ Year _____	
3. Are you Hispanic?	
☐ Yes	
☐ No	
4. Please indicate your race. <i>Check as many as you feel apply to you.</i>	
☐ Caucasian or white	
☐ African American or black	
☐ American Indian or Alaskan Native	
☐ Asian	
☐ Pacific Islander or Native Hawaiian	
☐ Prefer not to state	

Confidence (Circle answer that best describes you)						
How confident are you participating in physical activity during each of the following situations?		Not At All Confident	Somewhat Confident	Moderately Confident	Very Confident	Extremely Confident
1.	When I am tired.	1	2	3	4	5
2.	When I am in a bad mood.	1	2	3	4	5
3.	When I feel I don't have the time.	1	2	3	4	5
4.	When I am on vacation.	1	2	3	4	5
5.	When the weather is bad.	1	2	3	4	5
6.	Make time for at least 30 minutes of physical activity daily (like walking).	1	2	3	4	5

Social Support (Circle the answer that best describes you)						
How often in the last 30 days has your family or friends done the following?		Almost Never	Once in a While	Sometimes	Often	Very Often
1.	Encouraged you to do physical activity.	1	2	3	4	5
2.	Discussed how not doing physical activity is unhealthy.	1	2	3	4	5
3.	Reminded you to do physical activity.	1	2	3	4	5
4.	Shared ideas on how to get enough physical activity.	1	2	3	4	5
5.	Done physical activity with you.	1	2	3	4	5

Enjoyment				
(Circle the one answer that best describes you)		Disagree	No opinion	Agree
1.	I have more fun engaging in physical activity than doing other things.	D	N	A
2.	Engaging in physical activity is the thing I like to do best.	D	N	A
3.	I wish I could engage in more physical activity than I get chance to.	D	N	A
4.	I usually prefer to watch rather than engaging in physical activity.	D	N	A
5.	I really like doing physical activity.	D	N	A

Barriers (Circle the response that best describes you.)					
Potential Barriers to Physical Activity		Strongly Disagree	Disagree	Agree	Strongly Agree
1.	Physical activity takes too much of my time.	SD	D	A	SA
2.	Physical activity tires me.	SD	D	A	SA
3.	Places for me to be physically active (e.g., parks, gyms) are too far away.	SD	D	A	SA
4.	I am too embarrassed to be physically active.	SD	D	A	SA
5.	It costs too much to be physically active.	SD	D	A	SA
6.	Exercise facilities do not have convenient schedules for me.	SD	D	A	SA
7.	I am fatigued by physical activity.	SD	D	A	SA
8.	My spouse (or significant other) does not encourage physical activity.	SD	D	A	SA
9.	Physical activity takes too much time from family relationships.	SD	D	A	SA
10.	I think people in exercise clothes look funny.	SD	D	A	SA
11.	My family members do not encourage me to exercise.	SD	D	A	SA
12.	Physical activity takes too much time from my responsibilities (e.g., school, work)	SD	D	A	SA
13.	Physical activity is hard work for me.	SD	D	A	SA
14.	There are too few places to be physically active	SD	D	A	SA

Outcome Expectancy (Mark either “Yes” or “No” for each question by circling the answer which best describes you)			
If I were to be physically active most days...		Yes	No
1.	...it would help me get or stay in shape.	Y	N
2.	...it would be boring.	Y	N
3.	...it would increase my ability to play sports.	Y	N
4.	...it would be fun.	Y	N
5.	...it would help me be healthy.	Y	N
6.	...it would result in injury.	Y	N
7.	...it would help me maintain my weight.	Y	N
8.	...it would embarrass me in front of others.	Y	N
9.	...it would give me energy.	Y	N
10.	...it would make me tired.	Y	N
11.	...it would help me make new friends.	Y	N
12.	...it would help me spend more time with my friends.	Y	N

Motivation (Circle the response that best describes your degree of agreement with the statements below)								
Statements		Not at All True		Somewhat True			Very True	
1.	I enjoyed doing physical activity very much.	1	2	3	4	5	6	7
2.	Physical activity was fun to do.	1	2	3	4	5	6	7
3.	I think physical activity is a boring activity.	1	2	3	4	5	6	7
4.	Physical activity does not hold my attention at all.	1	2	3	4	5	6	7
5.	I would describe physical activity as very interesting.	1	2	3	4	5	6	7
6.	I think physical activity is quite enjoyable.	1	2	3	4	5	6	7
7.	While I was doing physical activity, I was thinking about how much I enjoyed it.	1	2	3	4	5	6	7

Anthropometric and Physiological Testing (For Study Personnel Only)			
Height (cm)	Weight (kg)	Body Fat Percentage	Post-YMCA Step Test HR

Appendix H. Post-Intervention Use/Acceptability Survey

Facebook Page Survey

(NOTE: Below survey administered to the experimental and comparison groups at 12 week testing session)

- 1. How helpful would you consider the health education tips delivered to you via the Facebook page?**
 - a. Very Helpful
 - b. Helpful
 - c. Somewhat Helpful
 - d. Neither Helpful or Unhelpful
 - e. Somewhat Unhelpful
 - f. Unhelpful
 - g. Very Unhelpful
- 2. How many days a week/month did you implement at least one of the health education tips delivered to you via the Facebook page in daily life?**
 - a. Daily
 - b. 4-6 times weekly
 - c. 1-3 times weekly
 - d. 2 times per month
 - e. 1 time per month
 - f. Never

Polar M400 Survey

(NOTE: Below survey only administered to experimental group at 12 week testing session)

- 1. How useful did you perceive the Polar M400 Smartwatch to be in assisting you to monitor your physical activity participation?**
 - a. Very Useful
 - b. Useful
 - c. Somewhat Useful
 - d. Neither Useful or Unuseful
 - e. Somewhat Unuseful
 - f. Unuseful
 - g. Very Unuseful
- 2. How easy was the Polar M400 Smartwatch to use?**
 - a. Very Easy
 - b. Easy

- c. Somewhat Easy
- d. Neither Easy or Difficult
- e. Somewhat Difficult
- f. Difficult
- g. Very Difficult

- 3. What did you most enjoy about the Polar M400 Smartwatch?**

- 4. Are there improvements you would like to see to the Polar M400 Smartwatch?**

Appendix I. ActiGraph Wear Log and Instructions

Participant Name: _____

Date: _____

Assessment Period: Baseline 6-wk 12-wk

Participant ActiGraph Wear Time Log and Participant Wear Instructions

	Date	Time Placed on Wrist	Time Taken Off Wrist	Notes
Day #1				
Day #2				
Day #3				
Day #4				
Day #5				
Day #6				
Day #7				

Instructions for Wear

1. Please place the Actigraph on your right wrist upon waking in the morning and take off upon going to bed at night. *Note the corresponding times you placed the Actigraph on your right wrist and took the device off at night in the log above. Use the “Notes” section to state any large (> 30 min deviations in wear time on any given day).*
2. *Do not wear the Actigraph when performing any activity involving water.* This includes showers and swimming. While the Actigraph is waterproof, the Physical Activity Epidemiology Lab does not want to take this risk. Notably, sweat will not affect the device so please wear during all non-water-based physical activities.

3. Wear the Actigraph for 7 days as three weekdays and two weekend days of data collection are desired. ***If you miss a day, please email the study's investigator (Zachary Pope; popex157@umn.edu) promptly.*** Nonetheless, the Actigraph will have extra days “built in” to the assessment period.

Other Notes

- While the Actigraph's screen may be blank, the device is recording the intensity of your daily activities.
- ***Please notify the study's investigator (Zachary Pope; popex157@umn.edu) immediately if the Actigraph is in any way damaged, lost, or stolen.***

Appendix J. PAEL Device Use Agreement

PAEL Device Use Agreement

I _____ (print your name here) am accepting this device/equipment (list device/equipment name here: _____) from the Physical Activity Epidemiology Laboratory. I am aware of the device/equipment's purpose and its use. Further, I am aware that I am to not tamper with or damage this device/equipment in any way and will return the item to the Physical Activity Epidemiology Laboratory on the following date: _____ (insert return date here). If I am to damage or lose this device/equipment, I understand I could be held accountable for fixing/replacing the item.

Signature: _____

Date: _____

Appendix K. Sample ASA24 Email

[Insert Participant Name Here],

Hope this email finds you well! As we have discussed, this study is also interested in your eating habits. To collect this information, the study employs a food recall which requires you to state all the food you have eaten in the last 24 hours. The food recall is called the ASA24 and is easy to take as the recall walks you through each step of entering in the food you ate. Simply read the ASA24 instructions carefully and follow all the prompts.

To access your ASA24, please use [THIS LINK](#). You will be requested to provide a username and password of which I have listed below:

- **Username:** UMNDIS050
- **Password (Case-Sensitive):** Umndis!471

Please let me know if you have any questions/concerns. Notably, just answer the questions honestly and to the best of your ability. In other words, there are no right or wrong answers. A help guide is attached to this email just in case you need it. Finally, please remember that I will be asking you to complete 3 of these recalls over the course of the next 7 days of which I will contact you each time to complete. I promise that this is the most involved part of the study. All the best! Thanks

P.S. Please remember to wear your accelerometer :).

Appendix L. Twice-Weekly Health Education Tips.

The following tips will be provided twice a week on Monday and Thursday for 12 weeks to all study participants. Specifically, the intervention group and the comparison group will have their own Facebook groups through which these health tips will be provided.

Notably, each week includes one physical activity-related posting (Monday) and one nutrition-related posting (Thursday), with Social Cognitive Related health determinants targeted denoted after each tip in ***bold italics***. Moreover, the Self-Determination Theory-related determinants expected to be influenced by these tips are outlined in ***blue bold italics***.

Week One

Physical Activity Tip:

Did you know the American College of Sports Medicine states that the recommended 30 minutes a day of physical activity can be accumulated in 3 ten-minute bouts?! If you have an extra ten minutes, try going for a brisk walk or bike ride. Indeed, a quick physical activity break following a meal or at points of the day where you begin to feel tired can really go a long way! ***Social cognitive belief(s) targeted: Promoting Self-Efficacy, Decreasing Barriers; Self-determination theory constructs potentially influenced: Self-Determination/Autonomy, Competence***

Nutrition Tip:

Water is vital. Although recommendations put forth by numerous health organizations such as the Centers for Disease Control and Prevention and the American College of Sports Medicine state 6-8 cups a day is needed, this does not always hold true for all individuals. Therefore, if you are not confident in your ability to drink enough water, buy a good water bottle that can be used at the gym and during the day and drink each time you feel thirsty. Why is this important? Well, drinking water consistently throughout the day can help decrease your appetite and improve digestion while also replacing unnecessary excess kcalories from beverages such as soda and fruit juices that often contain added sugars. Given the preceding benefits, drinking more water may aid in improving health and even help you lose weight! ***Social cognitive belief(s) targeted: Promoting Self-Efficacy, Improving Outcome Expectancy; Self-determination theory constructs potentially influenced: Competence***

Week Two

Physical Activity Tip:

Social support is crucial to continued physical activity engagement. Thus, try to find a good friend willing to go “sweat it out” with you two or three times per week. Although your friend may not be able to join you for every workout, s/he may be able to provide company on the days where you are lacking the motivation to get to the gym. ***Social***

cognitive belief(s) targeted: Enhancing Social Support; Self-determination theory constructs potentially influenced: Relatedness/Social Interaction

Nutrition Tip:

Small changes in what you eat and drink daily will enhance the likelihood of sticking to your nutritional goals as opposed to wide, sweeping changes all at once. Indeed, you need to explore small dietary changes which best conform to your taste preferences and daily schedule while also promoting improved health. For instance, if you are busy with school or work and find you tend to purchase an unhealthy snack from a vending machine, perhaps consider a healthy snack replacement strategy where you pack a small plastic bag of carrots, cucumbers, and whole grain crackers. Not only will this alternative likely be lower in calories, but the foods will also contain more of the nutrients your body needs for good health. *Social cognitive belief(s) targeted: Promoting Self-Efficacy, Decreasing Barriers; Self-determination theory constructs potentially influenced: Self-Determination/Autonomy, Competence*

Week Three

Physical Activity Tip:

School work or your job stressing you out? Lucky for you, physical activity releases stress-reducing hormones such as endorphins into the bloodstream even during short 10-minute bouts of exercise. All the more reason to set aside a little time each day to be physically active! *Social-cognitive belief(s) targeted: Improving Outcome Expectancy; Self-determination theory constructs potentially influenced: Competence*

Nutrition Tip:

Desire to introduce more fruits and vegetables into your diet but worried about these fruits and vegetables going bad before you have had a chance to eat them? Consider a trip down the freezer aisle at your local grocery store. Specifically, look at the frozen fruit and vegetable options available to you! Indeed, most fruits and vegetables are available as frozen options and are every bit as nutritious as their non-frozen counterparts—and sometimes cheaper as well. Just remember to look for frozen fruit and vegetable options which do not have added sauces (e.g., gravy) or extra butter/cream and salt. *Social cognitive belief(s) targeted: Promoting Self-Efficacy, Decreasing Barriers; Self-determination theory constructs potentially influenced: Self-Determination/Autonomy, Competence*

Week Four

Physical Activity Tip:

Worried about your motivation to exercise in the morning or that you will forget your exercise clothes as you head out the door? Place your workout clothes/shoes in front of the door you exit each morning. In this manner, you will have to move the clothes prior

to opening the door, acting as a reminder to be a little more physically active during the day or to not skip the gym in the evening. ***Social cognitive belief(s) targeted: Promoting Self-Efficacy, Decreasing Barriers*** *Self-determination theory constructs potentially influenced: Self-Determination/Autonomy*

Nutrition Tip:

Protein is important for numerous processes in the body. Not only is protein important for growth/repair of bodily tissues, but is instrumental in the proper functioning of hormones and enzymes as well. Foods like chicken, seafood, beans, eggs, and soy products are great lean sources of protein which can be introduced into the diet as part of a main dish (e.g., making a tuna salad or bean chili). Notably, consumption of protein-rich foods decreases appetite given the fact it takes longer for the body to break down the protein in these foods meaning protein might aid in controlling intake of excess calories. ***Social cognitive belief(s) targeted: Promoting Self-Efficacy, Improving Outcome Expectancy;*** *Self-determination theory constructs potentially influenced: Competence*

Week Five

Physical Activity Tip:

Again, social support is important to physical activity participation. If you are engaging in a new physical activity program, perhaps tell your family and close friends about your new program and related goals. Stating your plans/goals out loud not only increases the likelihood that you will continue this physical activity program, but your family and friends will surely ask about it at some point in the future meaning you may be held accountable for sticking to this program and achieving your health goals! ***Social cognitive belief(s) targeted: Enhancing Social Support;*** *Self-determination theory constructs potentially influenced: Relatedness/Social Interactions*

Nutrition Tip:

Foods like sour cream, cream, and regular cheese can be high in saturated and total fat. However, superb substitutes for the aforementioned foods are available in the form of low-fat yogurt, milk, and cheese, as well as soy alternatives—foods also often higher in protein content than their less healthy counterparts. Consider low-fat yogurt, milk, cheese, and soy alternatives to decrease saturated and total fat intake while also ensuring adequate intake of protein. ***Social cognitive belief(s) targeted: Promoting Self-Efficacy, Improving Outcome Expectancy;*** *Self-determination theory constructs potentially influenced: Competence*

Week Six

Physical Activity Tip:

One of the best ways to ensure you continue to participate in a physical activity program is finding an activity you enjoy. If you are an individual who prefers to work out alone,

perhaps swimming, running, or biking suits you the best. For individuals who prefer to workout with others, consider group exercise classes such as yoga or step aerobics such as Zumba or dancing. Additionally, do not be afraid to mix and match different types of exercise! If you are going to sweat, you might as well be doing something that interests you! ***Social-cognitive belief(s) targeted: Increasing Enjoyment, Enhancing Social Support; Self-determination theory constructs potentially influenced: Self-Determination/Autonomy***

Nutrition Tip:

Worried about a potluck or party derailing your goal of healthier eating? Keep in mind the following three tips. First, walk around the food table to see what options are available and decide upon what available foods are conducive to your nutritional goals and which are not. Second, ensure you create for yourself a colorful plate approximately half full of fruits and/or vegetables, with smaller portions of each food you choose. Eating foods of different colors will increase the variety of health-enhancing nutrients consumed while eating smaller portions of food will ensure you do not eat too much. Finally, consider water or unsweetened iced tea as drink options while at a potluck or party instead of sugar-sweetened and/or high-calorie options such as soda, juices, punch, or alcohol. In this way, you can still have fun with friends without worrying about derailing your health goals! ***Social cognitive belief(s) targeted: Promoting Self-Efficacy, Improving Outcome Expectancy, Decreasing Barriers; Self-determination theory constructs potentially influenced: Self-Determination/Autonomy, Competence***

Week Seven

Physical Activity Tip:

Crank those tunes! If music is something you know will get you motivated to engage in your workout, consider investing in some athletic-oriented headphones that are sweat resistant and capable of staying in your ears during exercise. Keeping an up-to-date playlist of your favorite songs will allow you to have a better workout. This is especially true of exercisers preferring to exercise indoors. However, if exercising outdoors, consider leaving the headphones at home and enjoying the sounds and scenery as use of headphones while exercising outdoors can put you in danger. ***Social-cognitive belief(s) targeted: Increasing Enjoyment; Self-determination theory constructs potentially influenced: Competence***

Nutrition Tip:

Coffee is a daily beverage for many. Yet, how an individual prepares their coffee can have a direct effect on their nutritional goals. Therefore, think about the following when getting your daily coffee. First, consider downsizing to a smaller drink, nixing whipped cream and caramel, and reducing or eliminating the addition of syrups to your drink. Second, if you like to add dairy to your coffee, look at adding low- or non-fat milk instead of whole fat milk. Not only will this substitution decrease caloric intake, but this

substitution will also reduce saturated and total fat intake. Finally, when purchasing a muffin or pastry, perhaps consider splitting it with a friend as these foods can be higher in calories. *Social cognitive belief(s) targeted: Promoting Self-Efficacy; Self-determination theory constructs potentially influenced: Competence*

Week Eight

Physical Activity Tip:

Journaling is a great way to increase the likelihood of engagement in physical activity! Writing down not only your workouts, but the feelings associated with those workouts forces you to reflect upon different aspects of your exercise session. This reflection can have a profound impact on your motivation to continue your physical activity program and your desire to continue to experience the mental and physical benefits coming about as a result of participating in a regular physical activity routine. Try journaling today!

Social-cognitive belief(s) targeted: Improving Outcome Expectancy, Improving Outcome Expectancy; Self-determination theory constructs potentially influenced: Competence

Nutrition Tip:

Limit eating out to once a week. When eating out, however, consider how you might improve the health of your order. For instance, you could look for entrees featuring vegetables such as a chicken or vegetable stir-fry. Further, you might consider ordering steamed options as steamed foods are often lower in saturated and total fat than fried foods. Finally, asking for additional oils or sauces on the side is a request many restaurants gladly accommodate of which will allow you more control of the caloric, salt, and fat content of your food. *Social cognitive belief(s) targeted: Promoting Self-Efficacy, Decreasing Barriers; Self-determination theory constructs potentially influenced: Self-Determination/Autonomy, Competence*

Week Nine

Physical Activity Tip:

Did you know that literature states that around 60 days is needed to make a new behavior a habit? Think about physical activity in the same manner. If you can engage in physical activity on a regular basis—say four times a week—over the course of two months, you will likely end up craving the good feeling physical activity provides when you miss a workout. Therefore, think about setting a start date and a follow-up date two months out. Then, plan to exercise a specified number of times per week over the next two months. At the follow-up date, reflect upon what your physical activity program means in the context of your daily routine. You will likely find that physical activity is something that you now crave and cannot do without! *Social-cognitive belief(s) targeted: Promoting Self-Efficacy, Decreasing Barriers, Improving Outcome Expectancy; Self-determination theory constructs potentially influenced: Self-Determination/Autonomy, Competence*

Nutrition Tip:

Fiber is a nutrient which aids in decreasing levels of low-density lipoprotein cholesterol (i.e., the “bad” cholesterol) and promoting increased high-density lipoprotein cholesterol (i.e., the “good” cholesterol) while also promoting better digestive functioning. One way to ensure adequate intake of fiber is to increase consumption of foods high in whole grains. Foods such as bread, rice, oats, and granola can be great sources of whole grains; however, not all of these foods are created equal. To ensure the food you are considering purchasing is high in whole grains, look for terms such as “100% whole grain” or “100% whole wheat” on the ingredient label. Not only will these foods provide higher fiber per serving, but they will also possess greater amounts of nutrients per serving compared to more refined grains. ***Social-cognitive belief(s) targeted: Promoting Self-Efficacy; Self-determination theory constructs potentially influenced: Competence***

Week Ten

Physical Activity Tip:

Individuals new to a physical activity program often believe that they need to exercise every day to receive the benefits of exercise. However, this could not be further from the truth! Rest and recovery is a good thing. Consider exercising a maximum of 4 days a week if you are just beginning a physical activity program. Further, consider splitting these 4 days up over the course of the week to allow for your body to recover. For example, you could work out on Monday and Tuesday, rest on Wednesday, workout on Thursday and Friday, and take the weekend off. This rest will allow your body to experience the maximum amount of adaptations from your workouts! ***Social-cognitive belief(s) targeted: Promoting Self-Efficacy, Decreasing Barriers, Improving Outcome Expectancy; Self-determination theory constructs potentially influenced: Self-Determination/Autonomy, Competence***

Nutrition Tip:

Got a “sweet tooth”?! If so, you are not the only one! The good news is, your sweet tooth does not have to adversely affect your pursuit of healthier eating behaviors. Indeed, consider making a fruit salad or yogurt parfait for a cold dessert or, for a delicious hot dessert option, baked apples with cinnamon as a topping is a great choice. What a great way to blend the enjoyment of satisfying a sweet tooth with engaging in more nutritious eating! ***Social-cognitive belief(s) targeted: Promoting Self-Efficacy, Increasing Enjoyment, Decreasing Barriers; Self-determination theory constructs potentially influenced: Competence***

Week Eleven

Physical Activity Tip:

Sleep may not seem important to physical activity, but it is. Not getting enough sleep is a sure-fire way to experience decreases in motivation for engaging in physical activity.

Therefore, aim for 6 to 8 hours of sleep each night. Moreover, try to cut out all screen time in the 10 to 15 minutes prior to going to sleep as watching TV or using your computer/smartphone to cruise social media or read the news decreases the body's ability to produce melatonin, a key sleep hormone. Finally, consider removing any TV from the bedroom and/or not playing music while you sleep as this background noise can actually decrease sleep quality. Making these small changes can go a long way in helping you feel more rested and ready to engage in physical activity (and life) the next day! ***Social-cognitive belief(s) targeted: Promoting Self-Efficacy, Decreasing Barriers; Self-determination theory constructs potentially influenced: Competence***

Nutrition Tip:

Look at your plate. What do you see? Ideally, you should see half your plate as including fruit and/or vegetables. Fruits and vegetables include nutrients vital to good health. Further, and more specifically, fruit can be a great natural substitute for candy or other dessert foods while many vegetables provide fiber important to the promotion of proper blood lipid levels (e.g., cholesterol). Notably, when eaten in proper amounts, fruits and vegetables are often lower in calories than other sides included with a meal. ***Social-cognitive belief(s) targeted: Promoting Self-Efficacy; Self-determination theory constructs potentially influenced: Competence***

Week Twelve

Physical Activity Tip:

Face it, you have put in the time in the gym and, perhaps, even lost a little weight in the process. Consider a monthly or bi-monthly reward. This reward can be anything from the purchase of that one shirt that you have been dying to add to your wardrobe to a night out with your significant other. Yet, whatever the reward is, make sure that it does not derail your quest for better health and participation in physical activity. ***Social-cognitive belief(s) targeted: Improving Outcome Expectancy; Self-determination theory constructs potentially influenced: Self-Determination/Autonomy***

Nutrition Tip:

Healthy eating is always more fun with friends! Consider a “Healthy Cooking Night” with friends where each individual is asked to search for a healthy entrée, side, dessert or beverage to cook/bake. Once each individual has found a recipe for their aspect of the meal, spend the night together cooking and baking! Not only will this increase the likelihood of engagement in healthy eating behaviors, but it is promoting support between each individual for participation in healthier lifestyle behaviors! ***Social-cognitive belief(s) targeted: Promoting Self-Efficacy, Increasing Enjoyment, Promoting Social Support; Self-determination theory constructs potentially influenced: Relatedness/Social Interactions***

Appendix M. Experimental Group Facebook Page

A Healthier U Study Group!

- Secret Group
- About
- Discussion
- Members
- Events
- Photos
- Manage Group

Search this group

Join ▾

Notifications

+++ More

Shortcuts

- A Healthier U Study Gr...
- A Healthier U Study Gr...
- PAEL BCS PA Promotio...
- PAEL BCS PA Promotio...
- Friendsgiving 2016!!!
- Boanerges (Sons of Th...
- PAEL Breast Cancer Su...
- PAEL Physical Activity ...
- PAEL Physical Activity ...
- Marriage Community ...

Write Post

Add PhotoVideo

Add Live Video

More

PhotoVideo

Poll

Feeling/Activ...

Write something....

PhotoVideo

Poll

Feeling/Activ...

ADD MEMBERS

+ Enter name or email address...

MEMBERS

11 Members

SUGGESTED MEMBER \$

Hide

Friends

Gail Pope Wakefield

Shelby Porter

Arianna Lee Driver-Hoag

See More

INVITED

dennis731220@... Send Reminder

See More

DESCRIPTION

Add a Description

Zachary Pope

September 6, 2017

Hello! Welcome to the Healthier U Study Group! On this page you will receive twice-weekly physical activity and nutritious eating tips which you can easily integrate into your daily routine. I hope you can give most tips, if not all, a try! At the very least, please hit the "Like" button for each post to let me know you have read the post! Finally, do not be afraid to post within this group and support one another on your journey toward a Healthier U! Perhaps even post data from your Polar M400 smartwatch so we can see what you have been up to during this journey! Questions/concerns, please email me at popez157@umn.edu. All the best!

Appendix N. Comparison Group Facebook Page

A Healthier U Study Group!!

A Healthier U Study Group!!
Secret Group
About
Discussion
Members
Events
Photos
Manage Group

Search this group

Joined ▾ Notifications More

Shortcuts
A Healthier U Study Gr...
A Healthier U Study Gr...
PAEL BCS PA Promotio...
PAEL BCS PA Promotio...
Friends/iving 2016!!!
Boanerges (Sons of Th...
PAEL Breast Cancer Su...
PAEL Physical Activity ...
PAEL Physical Activity ...
Marriage Community ...

Write Post Add Photo/Video Live Video More

Write something...

Photo/Video Poll Feeling/Activ...

Pinned Post

Zachary Pope
September 6, 2017
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Questions/concerns, please email me at popez157@umn.edu. All the best!!

ADD MEMBERS
+ Enter name or email address...

MEMBERS
12 Members
You have 1 new member this week. Write a post to welcome them.
SUGGESTED MEMBERS
Gail Pope Wakefield
Shelby Porter
David Hendrick
See More

FRIENDS
Add Member
Add Member
Add Member
Add a Description
Tell members what this group is about.

Seen by 7
Nan Zeng and 8 others

Appendix O. Example Intervention Fidelity Emails

Note: [Bracketed] and **bolded** text indicates differences between the language used during the first and second wave participants given differences in the time of year (e.g., Fall and Spring. Further, intervention fidelity protocol were implemented during the fifth and eleventh weeks of the study when contacting participants regarding 6 week and 12 week testing, respectively.

Midterms Email to Experimental Group (3 weeks into the Study)

Hello, all!

Just a quick email to thank you each for participating in A Healthier U! It is so greatly appreciated. Notably, midterms can be stressful, with this part of the semester always seeming like a grind, but being aware of your health status and behaviors can go a long way to reducing stress and promoting good health.

My hope is that the Facebook health education tips thus far have been informational and simple enough to implement on a regular or semi-regular basis! At a minimum, please remember to keep "Liking" the posts so I know you have read them. Further, I hope you are finding the Polar M400 useful in keeping track of your daily physical activity! It is a simple, but powerful smartwatch.

No need to respond to this email. Simply checking in with you all. As always, if you need anything, please contact me directly! All the best! Thanks

9th Week Email to Experimental Group

Hello, all!

As I did earlier in the semester, I just wanted to thank you once more for participating in A Healthier U! Keep up the great work in reading and "Liking" the Health Education Tips I have continued to post. My hope is that the Polar M400 has also assisted in improving your health journey!

That said, I hope you have and continue to try and implement some of the Health Education Tips I have posted/will post. Additionally, I hope you have found the Polar M400 helpful too as you track you daily physical activity! I will contact each of you during the [second/third week] of [December/April] at which time we will schedule post-intervention testing so that you can finish with the Study and get paid for participation prior to [Christmas Break/Summer Break]. Until then, keep up the great work! All the best! Talk soon.

Midterms Email to Comparison Group (3 weeks into the Study)

Hello, all!

Just a quick email to thank you each for participating in A Healthier U!! It is so greatly appreciated. Notably, midterms can be stressful, with this part of the semester always seeming like a grind, but being aware of your health status and behaviors can go a long way to reducing stress and promoting good health.

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No need to respond to this email. Simply checking in with you all. As always, if you need anything, please contact me directly! All the best! Thanks

9th Week Email to Comparison Group

Hello, all!

As I did earlier in the semester, I just wanted to thank you once more for participating in A Healthier U!! Keep up the great work in reading and "Liking" the Health Education Tips I have continued to post.

Again, I hope you have and continue to try and implement some of the Health Education Tips I have posted/will post. I will contact each of you during the **[second/third week]** of **[December/April]** at which time we will schedule post-intervention testing so that you can finish with the Study and get paid for participation prior to **[Christmas Break/Summer Break]**. Until then, keep up the great work! All the best! Talk soon.