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LONGITUDINAL CLUSTERING OF HEALTH BEHAVIORS WITHIN THE FRAMINGHAM HEART STUDY

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LONGITUDINAL CLUSTERING OF HEALTH BEHAVIORS WITHIN THE

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ABSTRACT

Health risk behaviors (HRB) have been shown to impact non-communicable chronic disease (NCI) over the lifespan, which are among the leading causes of mortality within the United States. Treatment of NCI includes both pharmacological and behavior change intervention. Though behavior change recommendations are common in the treatment of NCI, our understanding of the long-term trajectory of HRB and how they cluster are not yet fully understood. The current study seeks to elucidate the clustering of specific health behavior changes over the lifespan, bolstering the potential for taking preventative measures as well as fostering positive health behavior change more broadly in a limited treatment setting. Data from the Framingham Heart Study were used to examine 4 health risk behaviors: tobacco use, alcohol misuse, fruit and vegetable intake, and physical activity. Methods: Data were analyzed using latent transition analysis to explore patterns of health behavior clustering as well as transition patterns of participants between clusters over time. Grouping variables of gender, age, and waist to height ratio were also included to explore potential moderating effects. Results: Three health behavior clusters were identified: unhealthy, healthy, and energy balance deficient. The unhealthy class had the highest likelihood of not meeting any of the guidelines for health behavior recommendations. Conversely, the healthy class had a high likelihood of meeting recommendations for all four HRB. The energy balance deficient class showed a high likelihood of meeting recommendations for alcohol and not smoking but were less likely than the healthy group to meet physical activity or fruit and vegetable recommendations. These clusters were consistent across timepoints while participant membership in clusters changed over time. Overall, participants were most likely to move into the healthy class from Time 1 to Time 2 and then most likely to move to the energy balance deficient class from Time 2 to Time 3. Gender and age were predictive of cluster membership at Time 1 and waist to height ratio was not a good predictor of cluster membership at Time 1. Conclusions: Health behaviors tend to cluster and these clusters tend to appear consistently over time. People tend to change their health behaviors and often change more than one. Behaviors most likely to cluster are addictive behaviors such as drinking alcohol or smoking tobacco, while physical activity and dietary intake may also cluster together. This information provides insight into the potential for improving healthy lifestyle behaviors when multiple health risk behaviors are present. Personal information, such as demographic characteristics, can have important implications for health behavior, but waist to height ratio may not be a reliable indicator for health behavior assumptions or recommendations.

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DEDICATION

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CHAPTER 1

Introduction

Chronic diseases are a persistent and growing healthcare cost, despite increased attention and efforts of healthcare providers to mitigate and treat this class of illness (Scarborough et al., 2011). In the United States, billions of dollars are spent each year through pharmacological and surgical treatments for the symptoms of these diseases. Unfortunately, treating the symptoms of type 2 diabetes, coronary artery disease, and many others do not lead to a reversal of the overall pathology of the disease. Although medications and visits to medical providers can help ameliorate symptoms as well as stave off catastrophic effects from chronic disease, it is an expensive and ineffective long-term treatment for chronic diseases (Herman et al., 2005).

As medical care and vaccinations have progressed, people are far less likely to die from a communicable disease or illness, and instead are most likely to die due to a noncommunicable chronic illness (NCI). An NCI is commonly referred to as chronic disease, or illnesses that are not spread by contagions, develop over a long period of time, are characterized by a gap between exposure to risk and adverse health outcomes (Currey & Fitzgibbon, 2009). The largest impact in the development of chronic disease related to behavior can be found in 4 health risk behaviors (HRB): dietary intake, physical activity, alcohol use, and tobacco use). Depending on the disease, someone may even be able to live a long time after diagnosis by incorporating minimal changes to their health behaviors. These HRB may also present differently based on a number of demographic variables, such as age, gender, or obesity status. This sort of variability in the course, prognosis, and magnitude of effects from a diagnosis of an NCI is one reason for the difficulty in managing the treatment recommendations from providers (Bains & Egede, 2011). Studies have shown that these behaviors may work in concert rather than independently, providing the stage for both widespread increases and decreases in more than one behavior through focused treatment of one (deRuiter, Cairney, Leatherdale, & Faulkner, 2014

It is widely accepted that a multidisciplinary team approach to the treatment of chronic disease is the best practice (Garvey et. al., 2016). Since health behaviors play a large part in the development of many preventable chronic diseases, behavior should be at the center of the treatment of these diseases. Prescription of health behavior modification or weight reduction is common practice among primary care and other health professionals, though these recommendations have had limited effectiveness (Ko et al., 2008). Unsuccessful health behavior change attempts can also make future health behavior change attempts less likely and more difficult, so understanding barriers to success for patients is paramount (Polivy & Herman, 2002; Prochaska, & Levesque, 2002).

Though research has demonstrated the effects of HRB on the development and course of chronic disease, our understanding of how these behaviors develop, change, and affect one another is limited. Furthermore, an understanding of how these presentations may differ based on personal factors like age, gender, and obesity status is important for personalization of interventions. Analysis of the course of behavior change rather than exclusively the progression of NCI like cardiovascular disease or type 2 diabetes can help illuminate gaps in care and strengthen intervention and prevention efforts. Understanding how these behaviors impact one another over time also allows for a more nuanced approach to population health through multiple behavior change.

Energy balance behaviors.

Dietary intake. Dietary intake adjustment is a common recommendation in response to the development of NCI such as diabetes, chronic heart disease, or obesity (Ko et al., 2008). One common measure of dietary quality is consumption of fruits and vegetables because they have been associated with an overall improvement in dietary quality (Thompson, Ferry Jr., Cullen, & Liu, 2016). The majority of Americans do not meet daily or weekly recommendations for fruit and vegetable consumption (Lee, Moore, Park, Harris, & Blanck, 2022). Dietary intake quality is complicated by a number of factors, but research shows that both short-term dieting and attempts at long-term dietary changes are common. Despite common efforts at dietary changes, environmental factors can affect one's ability to make sustainable changes to their dietary intake (Puhl, Moss-Racusin, Schwartz, Brownell, 2008). Research has shown that areas with a high density of fast-food chains, coupled with decreased access to grocery stores, have higher incidence rates of obesity (Fraser & Edwards, 2010; Morland & Evenson, 2009).

Physical activity. The World Health Organization (WHO) has specific guidelines for weekly physical activity which include 150–300 minutes of moderate-intensity aerobic physical activity, or at least 75–150 minutes of vigorous-intensity aerobic physical activity, as well as resistance training for muscle strengthening (Bull et al., 2020). Many benefits of physical activity have been identified by research on physical activity and range from improving physical health to higher overall well-being (USDHSS, 2008; Lee et al., 2012; Kaplan, 2000; McAuley, Blissmer, Marquez, Jerome, Kramer, & Katula, 2000). Even with the vast number of positive outcomes related to physical activity, most Americans do not engage in the recommended amount of physical activity, with 25% to 36% reporting no leisure-time physical activity at all (CDC, 2008). Much like dietary changes, attempts to increase physical activity are commonly recommended in primary care settings but are difficult to initiate and maintain (Keadle, McKinnon, Graubard, & Troiano, 2016). Since diet and exercise are important in preventing and treating NCI, it is important to note how these behaviors change and common factors that impact behavior changes over time.

Alcohol use. Alcohol use is associated with the development of over 60 diseases and is the second greatest disease burden in high income countries after tobacco use (WHO, 2009). The biggest gains to be made in reducing alcohol use in the service of reducing likelihood of developing NCI are found within moderate risk populations of drinkers. Moderate drinkers include a much larger segment of the population and are still exposed to the risks associated with alcohol (Drummond et al., 2004). Harm-reduction or brief interventions can be utilized by these teams with individuals who present to their appointments and would benefit from an early intervention preventing later acute or chronic problems (U.S. Preventive Services Task Force, 2010).

Tobacco use. Tobacco use remains the largest preventable cause of death, disease, and disability worldwide (WHO, 2011). Many factors contribute to the addictive nature of tobacco use and dependence, from the chemically addictive nature of nicotine, the behaviorally signaled habit and conditioning, to social and environmental aspects of initiation and continued use like appetite suppression and weight loss (Picciotto & Mineur 2014). Smoking has decreased considerably since its negative effects were first published by the Surgeon General in 1964, falling to 19% from 42.4% between 1964 to 2011 (CDC, 2012). However, because tobacco use remains the leading cause of preventable death in the U.S. and worldwide and is linked to the initiation of other HRB, it also remains a critical point of treatment for lowering the incidence rates of NCI.

Interplay of health risk behaviors

It is difficult to disentangle the onset and motivations for each HRB, and their impacts on one another are not well understood. Research shows that changing one HRB often leads to change in another (Perkins, et. al., 1993; Johnson, Paiva, Mauriello, Prochaska, Redding, & Velicer, 2014). Though some research is promising on the domino effects of changing HRB, results are variable in intervention effectiveness. In a Cochrane review of studies targeting physical activity and dietary change, only 3 of 21 studies achieved significant changes in both behaviors (Waters et al., 2011). Research on the interplay of outcomes of multiple HRB, as well as individual factors such as age, gender, or obesity status, continues to emerge and improve understanding of these processes.

Clustering. One aspect of improving understanding of multiple behavior change is to understand how certain behaviors, though distinct, may cluster together. In a recent review examining clustering of behaviors in the available literature, 24 of 43 available studies found a clustering of alcohol use and smoking, reinforcing the idea of addictive behaviors being related. Furthermore, 81% of the studies indicated a cluster of an absence of risk behaviors in which individuals tended to not engage in any HRB. Of the available 28 studies, 14 found that all 4 tended to appear together, while diet and physical activity clustered in 16 out of 36 available studies (Noble, Paul, Turon & Oldmeadow, 2015). The existing research on health behavior tends to show that every additional HRB tends to increase the risk for adding another one and that smoking is the most predictive of additional HRB (Prochaska & Prochaska, 2016; Noble, Paul, Turon & Oldmeadow, 2015). Two main clusters tend to show consistency across many studies, addictive behaviors (smoking and alcohol use) and health promoting behaviors (fruit and vegetable intake and physical activity) (Noble, Paul, Turon & Oldmeadow, 2015). Studies identifying clusters in health risk behaviors have either been cross-sectional in nature, single-timepoint analyses, or have not included all four HRB. Studies that included longitudinal cluster analysis of all four HRB will be an important next step in expanding our understanding of how behaviors may change together over time.

Treatment implications. Many behavior-change interventions have transferable skills that may apply to more than one behavior. Monitoring behavior patterns in sedentary behavior can help increase efficacy of interventions designed to increase physical activity (Gualtieri, Rosenbluth, & Phillips, 2016). Likewise, simply monitoring one's diet can lead to desired dietary changes (Patel, Brooks, & Bennet, 2019). In sum, understanding how risk-behavior change happens naturally over the lifespan can have important implications for increasing multiple behavior change treatment efficacy, improving lifestyle and health outcomes with an emphasis on impact and longevity. The current study seeks to fill a gap in the literature by furthering our understanding of how health behaviors cluster over several timepoints and how people may shift over time without specific intervention. This information can help identify risk profiles for health behavior and inform tailored, efficacious treatment strategies for patterns of health risk behavior rather than using interventions that treat these behaviors as if they happen independent of one another.

CHAPTER 2

Review of the Literature

The burden of noncommunicable chronic illness

The leading causes of death across the United States have changed substantially over the past 150 years (CDC, 2019). As medical care and vaccinations have progressed, people are far less likely to die from a communicable disease or illness, and instead are most likely to die due to a noncommunicable chronic illness (NCI). An NCI is commonly referred to as chronic disease or illness that is not spread by contagions, develops over a long period of time, is characterized by a gap between exposure to risk and adverse health outcomes, and usually includes multiple HRB (Currey & Fitzgibbon, 2009). Among the top ten leading causes of mortality are five NCIs: heart disease, cancer, chronic lower respiratory diseases, diabetes, and stroke (Heron, 2017). Depending on the disease, someone may even be able to live a long time after diagnosis with few changes to their health behaviors. This sort of variability in the course, prognosis, and magnitude of effects from a diagnosis of an NCI is one reason for the difficulty in managing the treatment recommendations from providers (Bains & Egede, 2011).

Chronic diseases are a persistent and growing healthcare cost, despite increased attention and efforts of healthcare providers to mitigate and treat this class of illness (Scarborough et al., 2011). Although medications and visits to medical providers can help ameliorate symptoms as well as stave off catastrophic effects from chronic disease, it is an expensive and ineffective long-term treatment for chronic diseases (Herman et al., 2005). It is widely accepted that a multidisciplinary team approach to the treatment of chronic disease is the best practice (Garvey et. al., 2016). The largest impact in the development of chronic disease related to behavior can be found in 4 health risk behaviors (HRB): dietary intake, physical inactivity, alcohol misuse, and tobacco use. Studies have shown that these behaviors may work in concert rather than independently, setting the stage for both widespread increases and decreases in more than one behavior through focused treatment of one (deRuiter, Cairney, Leatherdale, & Faulkner, 2014).

Obesity. Though obesity is merely one of myriad NCIs addressed in primary care, it is of critical importance to understand within the framework of chronic disease. Not only is it referred to as a disease of its own, but it is also seen as a manifestation of behavior and a strong predictor for the development of other chronic diseases (Ueland, 2019; Wadden, Butryn, & Wilson, 2007). Its recognition in 1999 as a global epidemic no doubt spurred research and treatment priorities to reflect the urgent need to address the issue (WHO, 2000). It is defined by the Centers for Disease Control and Prevention (CDC) using Body Mass Index (BMI). BMI is calculated by dividing a person's weight in kilograms by their height in meters squared. If an adult has a BMI over 30.0 they fall into the obese range, in which there are three subcategories (30 to <35, 35 to <40, and >40). The classes of obesity are used to describe a spectrum of risk, with those falling above 40 being categorized as class 3, severe, or extreme (NHLBI, 1998).

Though BMI is used consistently throughout medical literature and practice as a way to identify risk associated with obesity, key issues have been identified in its use (Nuttall, 2015). Firstly, it cannot incorporate lean body mass and tends to over-pathologize weight. Its ratio between weight and height presupposes a linear relationship between weight and adipose tissue, a key factor in the BMI's relationship to risk for chronic disease. Furthermore, because of a cultural focus and sensitivity regarding weight, it can highlight weight as a factor of health rather than the ratio of lean body mass (bone, muscle, organ tissue) to body fat. To more specifically measure visceral adiposity, a prominent risk factor in developing a wide range of NCI, measures like waist to height ratio provide a more appropriate estimate of adiposity in the abdominal cavity. Studies have shown this method of identifying early risk is more effective than BMI (Ashwell and Gibson, 2019; Yoo, 2016; Lee, Lee, Lee, Kim, 2016).

Obesity, with its direct relationship to a person's body weight, brings with it diagnostic and treatment challenges unique to such a diagnosis. Losing weight has a relatively simple physiological equation: the calories we expend must exceed the calories we take in (Strasser, Spreitzer, & Haber, 2006). A common misconception that leads to the stigmatization of individuals with larger bodies is that losing weight is as simple as eating fewer calories and expending more of them through activity. The domains of physical activity and dietary intake are a more complicated structure than a simple reduction and increase, not to mention the effects of metabolic rate in the actual number of calories a person burns. In fact, research shows that even effective weight loss with the maintenance of lean tissue can still result in a lower resting metabolic rate (Elliot, Goldberg, Kuehl, & Bennett, 1989). Interplay between behaviors as well as the complexity of factors influencing health behaviors makes appropriate behavioral prescriptions challenging. Furthermore, because obesity is stigmatized both in medical contexts and social contexts, people often draw conclusions about someone's behavior based on their body size, which does not tell the whole story about health behavior. In fact, studies have shown that healthy behavior change related to activity, fruits and vegetable intake, alcohol use and smoking behaviors can decrease mortality independent of baseline BMI (Matheson, King, Everett, 2012).

Health Behaviors

Energy balance behaviors. Because health behaviors play a large part in the development of many preventable chronic diseases, behavior should be at the center of the treatment of these diseases. Prescription of health behavior modification or weight reduction is considered best practice among primary care and other health professionals (Ko et al., 2008). The energy balance behaviors of dietary intake and physical activity are integral in managing the body's balance between energy intake and energy expenditure. Broadly, since a calorie surplus may be stored in the body in adipose tissue, weight loss goals are often pursued by establishing a calorie deficit. A calorie deficit creates an environment where the body is consuming fewer calories than it is expending, leading to utilization of stored energy in the body (Strasser, Spreitzer, & Haber, 2007). Though this process is well understood and reducing fat tissue can help improve NCI status, it is often a difficult goal for patients to meet. For example, when patients are told to lose weight using stigmatized terms, these comments are not effective interventions on their own and leave much of the process and behavior change skills unaddressed (Puhl, Peterson, Luedicke, 2013; Galuska, Will, Serdula, & Ford, 1999). Unsuccessful health behavior change attempts can also make future health behavior change attempts less likely and more difficult, so interventions that are mindful of the factors associated with behavior change specific to weight management are important (Polivy & Herman, 2002; Prochaska, & Levesque, 2002).

Dietary intake. Personal factors that affect dietary intake can range from genetic predispositions to temperament, disability, allergies, mental health, and many more that can provide complicating factors to consider when making dietary recommendations (Leng et. al., 2017). Dietary change recommendations are often given in the service of improving nutrient intake as well as reducing the number of calories consumed resulting in a caloric deficit and, ultimately, weight loss (Wharton et al., 2020). One dietary recommendation that can serve both purposes includes increasing fruit and vegetable intake. Because fruits and vegetables are both nutrient dense and low in calories, they are often used as a proxy for quality of dietary intake (Thompson, Ferry Jr., Cullen, & Liu, 2016). In fact, most Americans do not meet recommended daily guidelines of 5 fruits and vegetables, with 12.3% and 10% meeting guidelines, respectively, as of 2019 (Lee, Moore, Park, Harris, & Blanck, 2022). Even with low rates of compliance with dietary recommendations, most individuals with obesity attempt weight control, with about 66.7% of adults with obesity, 49.0% of overweight adults, and 26.5% of underweight or normal weight adults trying to lose weight between the years 2013-2016 (Martin, Herrick, Sarafrazi, & Ogden, 2018). Recommendations for dietary behavior change can be problematic for individuals with a history of disordered eating patterns, persistent failure when enacting dietary changes for weight loss, or dietary restrictions based on food sensitivities or allergies (Da Luz, Hay, Touyz, & Sainsbury, 2018). Dietary choice is often coupled with "right" and "wrong" food choices as well as "good" or "bad" foods, labels that tend to overemphasize personal responsibility and moralize food choice (Brownell et. al., 2010). Furthermore, individuals showing early signs of mental illness also tend to show a more unhealthy dietary intake than the general population, complicating any dietary advice they may receive from providers without a lens on the effects of mental illness on food consumption (Teasdale et al., 2019). Given the high incidence of disordered eating behavior, mental illness, stigma, and obesity within the United States, these factors are important in understanding long-term dietary behaviors.

Although weight from a cultural perspective is typically associated with personal discipline and willingness to make personal changes, environmental factors can have wide ranging impacts on dietary behavior (Testa & Jackson, 2019; Puhl, Moss-Racusin, Schwartz, Brownell, 2008). Research has shown that areas with a high density of fast-food chains, coupled with decreased access to grocery stores, have higher incidence rates of obesity (Cooksey-Stowers, Schwartz, & Brownell, 2017; Fraser & Edwards, 2010; Morland & Evenson, 2009). Individuals who are given easier access to calorie dense foods and limited access to nutrient dense options in their environment experience added barriers to changing their overall dietary quality (Walker, Keane, & Burke, 2010). Cultural factors play a large role in food selection as well, influencing what is acceptable, appropriate, and desirable in terms of food choice (Sobal & Bisogni, 2009).

Age and dietary intake. Dietary habits may be relatively stable in adulthood and can be established during childhood. In a study by Belot, Berlin, James, and Skafida, (2018), 285 low-income families were exposed to one of two different treatment groups: one that provided families with free groceries focused on healthful foods and another that simply asked families to reduce snacking and eat at regular times. The study found that the BMI for the children in the treatment groups had shifted significantly relative to the families in the control group. The children's eating habits and food preferences were also affected by the treatments. However, the adults in the families did not experience the same shifts in food preferences or regularity of food intake. The study highlights the complexity of dietary changes such that behavior changes do not necessarily lead to preference or habit changes in the long term for adults. Even when specific, healthful foods are provided for 12 weeks, the food preferences and eating regularity for adults were not affected. Much evidence suggests that dietary habits formed in childhood are somewhat persistent into adulthood (Graham & Jeffery, 2012). The stability of dietary habits into adulthood presents a complex and difficult challenge for long-term success in dietary changes once dietary habits are established.

Food literacy has played an important role in the dietary behavior for many families in the United States and is one of the most predictive factors of a poor nutritional diet, which seems to be an intersection of personal, cultural, and environmental factors at once (Mötteli, Keller, Seigrist, Barbey, 2016). For example, processed grain intake, including sugars and white grains, has increased to levels far exceeding any other time in history for the general population (Bentley, Ruck, & Fouts, 2020). Food literacy has been shown to influence dietary choices and provides a specific treatment goal to increase dietary guideline adherence in childhood and early adulthood (Kalkan, 2019). Dietary habits are the expression of a complex system of influential factors which may also include other health risk behaviors themselves. As health risk behavior habits are established, the path to health behavior change becomes increasingly difficult.

Gender and dietary intake. Men and women tend to get different levels of fruits and vegetables in their diet. Women have been more likely to eat any fruits and vegetables (Blanck, Gillespie, Kimmons, Seymour, & Serdula, 2008) and further are more likely to meet dietary guidelines concerning fruits and vegetables (Thompson, Yaroch, et. al., 2011). Explanations for the gender different in fruit and vegetable intake include nutritional knowledge (Crawford and Baghurst, 1990; Parmenter, Waller, Wardle, 2000), childhood differences (Reynolds, Hinton, Shewchuk, Kickey, 1999), marketing, and particularly current pressure for women to meet cultural expectations of "thinness" ideals (Fagerli and Wandel, 1999).

Obesity and dietary intake. Dietary intake and obesity status tend to have a reciprocal relationship. Studies have found that foods prepared away from home are often associate with eating fewer fruits and vegetables (Todd, Mancino, and B.-H. Lin, 2010). This interaction between dietary intake and obesity is clear and has an impact on both the availability of nutritious foods for obese individuals as well as the risk for developing obesity within these communities (Charreire et al., 2010). Food availability is just one of the factors that may lead to diet-cycling by overweight individuals, or moving back-and-forth from sustainable and unsustainable dietary habits directed at weight loss (Mehta, Smith Jr, Muhammad, & Casazza, 2014). Overall, overweight individuals tend to consume fewer fruits and vegetables on average when compared to individuals with a BMI in the 18.5-24.9 range (Pérez, 2002).

Physical activity. Physical activity is a key component of managing long term NCI development because it impacts so many functions throughout the body. Even though physical activity is an important aspect of health maintenance, its prominence in daily life has shifted in recent history. One major impact on the role of physical activity in daily life was industrialization and overall lifestyle change in recent history that has decreased opportunity for regular physical activity. The workforce has become far more sedentary and much less physically active over the past 70 years (Brownson, Boehmer, &

Luke, 2005). Even before the more recent changes in the labor force, advancements in automation and communication have not only made routine sedentary behavior more possible but also more enjoyable. Today, individuals must make choices about the amount of physical activity in which to engage over the course of a week. The United States Department of Health and Human Services (USDHHS) has specific guidelines for weekly physical activity, recommending at least 150 minutes per week of moderate-intensity, or 75 minutes of vigorous intensity, physical activity per week, including muscle-strengthening activities 2 days per week for adults (USDHHS, 2008).

Regular engagement in physical activity has also been shown to result in substantial improvements in health, psychological, and cognitive well-being, overall quality of life, and lower health care costs (Lee et al., 2012; Kaplan, 2000; McAuley, Blissmer, Marquez, Jerome, Kramer, & Katula, 2000). Even with the vast number of positive outcomes related to physical activity, most Americans do not engage in the recommended amount of physical activity, with 25% to 36% reporting no leisure-time physical activity at all (CDC, 2008).

Because physical activity generally reflects a dose-response curve, any physical activity is better than none (Brown, Carroll, Workman, Carlson, & Brown, 2014). Related to physical activity, exercise is a structured, planned, and series of repetitive movements in the service of improving or maintaining physical fitness (Caspersen, Powell, & Christenson, 1985). Physical fitness is also a component of health that is often misconstrued to be representative of or necessary for physical health. This confusion often leads to misleading cultural values around health and appearance expectations (Saguy & Gruys, 2010). While the pursuit of physical fitness often results in improvements to physical health, peak physical fitness is not necessary for long-term health. In fact, the pursuit of physical fitness can, at times, impede and negatively affect overall physical health (Yuan et al., 2018; Delimaris, 2014). This conflation between physical fitness and overall physical health can promote misleading beliefs about the requirements for engaging in sustainable, healthy physical activity for many.

Interest in physical activity is personal and multi-faceted, including aspects like body-image, health-related goals, reaching a fitness goal (e.g., training to run a race) and many others (Lindwall et al., 2017). People are often more motivated to exercise in pursuit of a positive body image rather than a focus on health (Homan & Tylka, 2014). Confidence in one's ability to perform or enjoy exercise plays an important role in whether it is initiated in the short term (McAuley & Blissmer, 2000; Salmon, Owen, Crawfor, Bauman, & Sallis, 2003). Prior and current participation in physical activity are correlated, showing us that if people are physically active in childhood or adolescence they are more likely to be physically active in adulthood (Kjønniksen, Anderssen, & Wold, 2009). As with dietary changes, changes in physical activity levels are facilitated by goal-setting, education about benefits of physical activity, and increasing opportunities to engage in physical activity. Furthermore, feedback, social support, and problem solving also bolster continued participation in physical activity behavior (Brassington, Atienza, Perczek, DiLorenzo, & King, 2002; Carels et al., 2005; Marcus at al., 2000; Rejeski et al., 2003).

Age and physical activity. Physical activity is likely to change over the lifespan and decrease as a person ages but increasing physical activity during childhood and adolescence can be an indicator for physical activity levels later in life (Taylor, Blair, Cummings, Wun, & Malina, 1999; Trudeau, Laurencell, Tremblay, Rajic, & Shephard, 1999). Because older adults are the fastest growing age group in the United States (U.S. Census Beurau, Population Division, 2008; USDHHS, 2010), studying how physical activity habits change in this population is supremely important. Increased bone density, lower risk of hip fracture, improved sleep quality, reduced central adiposity, lower risk of lung and endometrial cancers, weight maintenance following weight loss, and functional health improvements in older adults are among the benefits elucidated by research on physical activity (USDHSS, 2008). Not only are adults over 65 at the highest risk for development of NCI, they are the ones for whom behavior is most difficult to change due to myriad physical challenges and barriers to health behavior change (Atella et al., 2019; Costello, Kafchinski, Vrazel, & Sullivan, 2011). Furthermore, the guidelines and definitions of physical activity have changed throughout the last century. From an explosion of exercise and body building in the 1970s to the rise of "fitness" culture in the 2000's, participation in physical activity has not always been required or explicitly recommended (Blair, LaMonte, & Nichaman, 2004). As research and recommendations have progressed, keeping up with recommended changes may have been difficult across the lifespan. Physical inactivity is reliably associated with the development of NCI and older adults are among the most inactive of any age group (White, Wojcicki, & McAuley, 2012).

Gender and physical activity. Men and women also seem to participate in physical activity at different rates. Across the lifespan, females tend to participate in less physical activity and engage in more sedentary leisure time activities than men (Caspersen, Pereira, and Curran, 2000; Hickey and Mason, 2017). Men and women also experience weight stigma differently, which can contribute to different levels of physical activity participation. In a study by Sattler and colleagues (2018), women experience higher levels of weight stigma which led to lower levels of physical activity engagement. Conversely, when men experienced weight stigma, they were observed to engage in higher levels of physical activity. Social and cultural factors seem to impact men and women differently in terms of physical activity participation.

Obesity and physical activity. Due to stigmatization of larger bodies in both cultural and medical settings, an individual's body size is often accepted as a way to draw conclusions about their participation in weight management strategies (Puhl, & Heuer, 2009). However, most individuals are likely to have attempted to lose weight through dieting and other strategies (Yaemsiri, Slining, & Agarwal, 2011; Serdula, Mokdad, Williamson, Galuska, Mendlein, & Heath, 1999). Data shows that higher-weight individuals may have less motivation to participate in physical activity for a number of reasons, discomfort in participating in exercise and lack of time being the most common (Eagan, Mahmood, Fenton, Redziniak, Kyaw Tun, Sreenan, McDermott, 2013). Even when individuals can exercise more, physical activity may not actually lead to a significant weight reduction on its own (Caudwell, Hopkins, King, Stubbs, & Blundell, 2009). These factors have impacted both the difficulty in establishing tailored treatment recommendations for higher-weight individuals as well as caused the options for sustained, consistent weight reduction through exercise to be limited. The understanding of the impacts of obesity on physical activity have been incomplete and exploring physical activity levels in higher-weight people may shed light on where treatment recommendations are falling short.

Addictive Behaviors

Like energy balance behaviors, addictive behaviors are related to natural bodily functions in their own way: one must drink and breathe in order to survive. A main difference between addictive behaviors and energy balance behaviors, however, is regulation. Alcohol use and tobacco are heavily regulated substances, including legal restrictions on age of use, establishment use regulations, and, in the case of alcohol, ability to operate machinery during use. These addictive behaviors can contribute to the development of the NCI most commonly treated in the U.S., whether directly or indirectly.

Alcohol misuse. Alcohol misuse is associated with the development of over 60 diseases and is the second greatest disease burden in high income countries after tobacco use (WHO, 2009). Alcohol use at a young age predicts long-term alcohol use, which contributes to NCIs over the lifespan (Ohannessian, Finan, Schulz, & Hesselbrock, 2015). The biggest gains to be made in reducing alcohol use in the service of reducing likelihood of developing NCI are found within moderate risk populations of drinkers. Moderate drinkers include a much larger segment of the population and are still exposed to the risks associated with alcohol (Drummond et al., 2004). While specialized treatment is and should be available for heavy and high-risk alcohol users, interventions for moderate alcohol use may remain with primary care and integrated care treatment teams. Harm-reduction or brief interventions can be utilized by these teams with individuals who present to their appointments and would benefit from an early intervention preventing later acute or chronic problems (U.S. Preventive Services Task Force, 2010).

Alcohol use can contribute to disease processes in secondary ways as well. Because of the high calorie count found in many alcoholic beverages, they are a contributing factor to obesity outcomes as they relate to overall energy balance (Shelton & Knott, 2014). Alcohol use is also associated with decreased inhibition, often contributing to high caloric intake of foods after becoming inebriated (Christiansen, Rose, Randall-Smith, & Hardman, 2016). While alcohol use has been associated with increased physical activity in college students, these behaviors are thought to be compensatory in nature rather than complementary (Abrantes, Scalco, O'Donnel, Minami, & Read, 2017). This compensatory relationship can further complicate energy balance behaviors and cause instability long-term for body image, calorie intake, and reasons for physical activity.

Age and alcohol misuse. The US population overall is aging and, as the average age of Americans has increased, so has the prevalence of alcohol misuse in older adults (Han, Moore, Sherman, Keyes, & Palamar, 2017). Many barriers exist to alcohol use reduction in later adulthood and include drinking for social enjoyment, self-medication of physical or mental health, or drinking as a part of established social norms (Kelly, Olanrewaju, Cowan, Brayne, & Lafortune, 2018). Furthermore, prevalence of drinking does not consistently decline according to older age (Wilsnack, Wilsnack, Kristjanson, Vogeltanz-Holm, and Gmel, 2009). Understanding the health risk behaviors in older adults as well as factors associated with decreasing these behaviors is key to developing efficacious treatments to reduce mortality associated with drinking and other health risk behaviors.

Gender and alcohol misuse. Men throughout the lifespan tend to drink alcohol at a higher rate than women in both lower and higher volumes. Furthermore, women have been shown to have a higher likelihood of quitting alcohol use than men, and men are more likely to show higher-frequency drinking than women (Wilsnack, Wilsnack, Kristjanson, Vogeltanz-Holm, and Gmel, 2009). A study by Wade (2020) has shown that being male and having a masculine gender orientation is associated with heavy episodic drinking among White Americans.

Obesity and alcohol misuse. Scientists and health experts agree that the effects of problematic drinking can exacerbate the health risks associated with obesity (Mahli, Hellerbrand, 2016; Traversy, Chaput, 2015). Heavy drinking habits are associated with higher risk for developing obesity, but studies have been conflicted on the strength of the association and have identified it as a weak predictor for obesity when compared to other factors (Traversy, Chaput, 2015). Frequent and heavy alcohol use can have negative effects on weight loss attempts, affecting a wide range of factors impacting dietary intake, caloric intake specific to alcoholic beverages consumed, maintenance of physical activity, and other physical symptoms associated with heavy alcohol use (Kase, Piers, Schaumberg, Forman, & Butryn, 2016).

Tobacco use. Tobacco use remains the largest preventable cause of death, disease, and disability worldwide (WHO, 2011). Many factors contribute to the addictive nature of tobacco use and dependence. The chemically addictive nature of nicotine, the behaviorally signaled habit and conditioning, and social and environmental aspects of initiation are important in understanding nicotine addiction (Cohen, McChargue, Cortez-Garland, Prensky, & Emery, 2003). Continued use can even be spurred by seemingly useful side effects such as appetite suppression and weight loss (Picciotto & Mineur 2014). Nicotine addiction operates on a combination of positive reinforcement schedules, namely mood enhancement and avoidance of withdrawal symptoms (Dani & Heinemann, 1996). Along with choices to use nicotine because of its metabolic and appetite-suppressing side-effects, others simply want to control their anxiety symptoms and feel the sensation of pleasure. The sensation of relief is often actually linked with withdrawal modulation, which happens each time a smoker receives a dose of nicotine. This method of avoiding the sensations that accompany withdrawal (irritability, depressed mood, restlessness, anxiety) is effective and part of the reason nicotine cessation is such a difficult process (Hughes & Hatsukami, 1986).

Smoking has decreased considerably since its negative effects were first published by the Surgeon General in 1964, falling to 19% from 42.4% between 1964 to 2011 (CDC, 2012). Many factors have contributed to this decline, including taxes, workplace and public smoking bans, and de-normalization (and stigmatization) of smoking behavior. However, because tobacco use remains the leading cause of preventable death in the U.S. and worldwide as well as its link to the initiation of other HRB, it also remains a critical point of treatment for lowering the incidence rates of NCI.

On an individual level, treatments also must focus on chemical, behavioral, and social aspects of tobacco dependence. Cessation attempts without any sort of assistance or focused intervention typically relapse at a rate of about 95% (National Institutes of Health, 2006). The most effective individual tobacco cessation interventions utilize a number of components, including nicotine replacement therapies, cognitive and behavioral strategies, and continued quit attempts. A minimally intensive intervention recommended by the Public Health Service is the 5A model developed by Fiore and colleagues (2008). The 5A model stands for: Ask about tobacco use, Advise tobacco users to quit, Assess willingness to make a quit attempt, Assist with cessation, and Arrange follow-up. This model is often modified to simply Ask, Assist, and Referral to more intensive treatment, which may involve individualized, tailored treatment interventions. The most effective individual cessation programs include both intensive counseling sessions and a regiment of nicotine replacement therapy (Fiore et al., 2008). While both have been shown to be effective on their own, the combination is able to effectively attenuate to multiple aspects of nicotine addiction better than either approach alone.

Age and tobacco use. Tobacco use tends to start during teenage years and, much like alcohol use, current use is correlated with prior use (USDHHS, 2012). Smoking prevalence tends to decrease with age due to a generally early age of onset, quitting, and health complications as people age (Sachs-Ericsson, Schmidt, Zvolensky, Mitchell, Collins, Blazer, 2009). Although initiation of tobacco use tends to be in teenage years, all ages are appropriate targets for smoking cessation interventions (Kviz, Clark, Crittenden, Warnecke, Freels, 1995). An important factor associated with smoking cessation in older adults is psychological distress associated with health problems, which tends to impact motivation and a respective smoker's stage of change regarding quitting (Sachs-Ericsson et al., 2009).

Gender and tobacco use. Tobacco use has generally differed between men and women, with men having a higher likelihood of being smokers (King, Dube, Tynan, 2012). Reasons for tobacco use may also differ between men and women, with some evidence showing that men are also more likely to quit than women (Wetter, Kenford, Smith, Fiore, Jorenby, Baker, 1999). Some reasons for disparities in quit rates between men and women may be impacted by societal images of "thinness" for women, who may perceive benefits from metabolic changes associated with nicotine use as well as its appetite suppressing effects (Bloom et al., 2020).

Obesity and tobacco use. Tobacco use has biological effects that impact weight control, including suppressing appetite, heightened metabolism, and the experience of stress reduction (Hu, Yang, & Li, 2018). These factors impact the willingness for individuals to quit smoking, especially if a person is using smoking as a weight-control strategy and is under the age of 30 (Weekly III, Klesges, Reylea, 1992; Wee, et al., 2001). However, despite this correlation with weight and fear of weight gain, smokers of all ages who are trying to lose weight are more likely to also want to quit smoking than smokers who are not trying to lose weight (Wee et al., 2001). This alludes to the idea of HRB coinciding and clustering when health improvement is the overall goal.

Interplay of health risk behaviors

It is difficult to disentangle the onset and motivations for each HRB, and each may contribute to the other in unforeseen ways. Research shows that changing one HRB often leads to change in another. In one 3-year prospective study by Perkins and colleagues (1993), individuals who quit smoking significantly increased their physical activity, while individuals who continued smoking did not. When progress on one weight-related behavior, individuals are up to 1.5 times more likely to make progress on another (Johnson, Paiva, Mauriello, Prochaska, Redding, & Velicer, 2014). Taking action on making changes in one health behavior can lead to individuals progressing into the “action” stage of change on other health-related behaviors (Paiva et al., 2012). Though some research is promising on the domino effects of changing HRB, results are variable in intervention effectiveness. In a Cochrane review of studies targeting physical activity and dietary change, only 3 of 21 studies achieved significant changes in both behaviors (Waters et al., 2011). Research on the interplay of outcomes of multiple HRB continues to emerge and improve understanding of these processes.

Clustering. One aspect of improving understanding of multiple behavior change is to understand how specific health behaviors cluster together. A study by Rabel and colleagues (2019) sought to elucidate latent clusters of HRB in a sample of 4,238 participants from Southern Germany (51% female) with an average age of 49.2 (*SD* = 13.9). Data was collected at baseline and follow-up was conducted approximately 7 years later. The results revealed three clusters: one healthy cluster, one cluster that was moderately healthy and risky drinkers, and a cluster that was overall more likely to have more risk behaviors but more activity. This study highlights the complicated relationship between these health behaviors as they are sometimes viewed as a balance, with some health behaviors balancing out some health risk behaviors, such as in the second and third clusters. In another study identifying the patterns of health risk behavior presentations using a national survey in Germany, over half the participants presented with 2 or more HRB at the time of their contact in the survey and the most common combination was overeating and lack of physical activity (John, Hanke, & Freyer-Adam, 2018). Though “overeating” was identified as a HRB in the study, it was operationalized as participants presenting as overweight and the researchers did not specifically assess for dietary quality or dietary behaviors. This study shows the wide range of approaches being used to understand clustering health risk behaviors and the lack of nuance that often appears in research attempting to deepen understanding of presentations of HRB. Researchers have also utilized cross-sectional data to identify health behavior clusters across the lifespan. Pronk and colleagues (2004) identified clusters of HRB in a sample of children, adults, and older adults using dietary quality, weight status, drinking status (in adults), physical activity levels, and smoking status as their focus of health risk behavior. The study showed a less than 15% chance that participants would meet recommended guidelines on all areas of health behavior and that adolescents were most likely to meet these recommendations (14.5%) and adults were least likely (10.8%). Another study by Poortinga (2007) examined clusters of HRB and identified that smoking and heavy drinking tended to cluster with low fruit and vegetable intake. This is more evidence that physical activity may act as a compensatory behavior for some people participating in health risk behaviors, or that these behaviors may be more prevalent in those with labor-intensive occupations. The study also showed a tendency for people to present with all four HRB or none, showing a potential focus on overall "health" rather than changing specific behaviors for a specific health outcome.

The presentation of health behavior clusters is not uniform or homogenous throughout the literature. In a recent review examining clustering of behaviors in the available literature, 24 of 43 available studies found a clustering of alcohol use and smoking, reinforcing the idea of addictive behaviors being related. Furthermore, 81% of the studies indicated a cluster of an absence of risk factors in which individuals tended to engage in HRB at very low rates. Of the available 28 studies, 14 found that all 4 tended to appear together, while diet and physical activity clustered in 16 out of 36 available studies (Noble, Paul, Turon & Oldmeadow, 2015). The existing research on health behavior tends to show that every additional HRB tends to increase the risk for adding another one and that smoking is the most predictive of additional HRB (Prochaska & Prochaska, 2016; Noble, Paul, Turon & Oldmeadow, 2015). Two main clusters tend to show consistency across many studies, addictive behaviors (smoking and alcohol use) and health promoting behaviors (fruit and vegetable intake and physical activity) (Noble, Paul, Turon & Oldmeadow, 2015). Studies thus far have focused on cross-sectional methods to identify clusters of health behavior, but an important next step in understanding the course of HRB clusters is to study their relationship longitudinally.

The phenomenon of multiple behaviors changing simultaneously has been referred to as coaction and it has been observed in many studies examining multiple behavior change in Transtheoretical Model (TTM) studies (Johnson et al., 2008; Mauriello et al., 2010; Prochaska et al., 2004, 2005). Other evidence suggests that coaction likely results from the stage-tailored treatment style of the online TTM interventions, as control groups may see reductions in one but not multiple risk behaviors (Woolcott, Disman, Motl, Matthai, & Nigg, 2013). It is also true that TTM-tailored interventions can be conducive to coaction even without direct treatment to specific dysfunctional HRB. One study showed significant improvements in smoking and alcohol use when the direct treatment intervention was related to energy balance behaviors (Velicer et al., 2013).

In sum, the efficacy of an intervention designed to help change one health-risk behavior likely relies on many of the same principles needed to change others, which is especially true if the behaviors are related. Furthermore, compounding effects of focus on broader health goals can permeate more than one risk behavior at a time. Understanding how HRB change happens naturally over the lifespan can have important implications for increasing multiple behavior change treatment efficacy, improving lifestyle and health outcomes with an emphasis on impact and longevity.

Current study

The study seeks to identify ways in which HRB cluster and whether those clusters are persistent over time. The longitudinal nature of the data in the current assessment can provide information on both the presence and stability of HRB clusters in middle age as well as changes to membership in these clusters as individuals enter later stages of their life. This information can not only lead to more efficacious and impactful treatment strategies, but it can also help develop maximally effective preventative endeavors aimed at behaviors that may more substantially affect the development of or reduction of other HRB. The current analysis will also serve to replicate studies that show clustering of HRB based on addictive and energy balance properties of the behavior.

The study contains four main research questions. First, will health risk behaviors show consistent, homogenous clusters similar to previous research (Noble, Paul, Turon & Oldmeadow, 2015)? Second, will the latent clusters of behavior appear across the time series? Third, how does membership in the clusters change over time? Finally, do the demographic characteristics of age, gender, and adiposity (waist to height ratio) moderate membership in behavior clusters as well as transition probabilities between clusters over time?

CHAPTER 3

Methods

Data were obtained from the National Heart Lung and Blood Institute (NHLBI) following a request for use and approval from BioLICC. Before data were made available, Institutional Review Board expedited approval was obtained and shared with BioLICC.

Framingham study

The Framingham Heart Study (FHS) was initiated in 1948 by the National Heart Institute, which is now known as NHLBI. Its objective was to identify common factors that contribute to the development and course of CVD. The initial sample of 5,209 was comprised of participants from the age of 30 to 62 and was meant to follow them over the lifespan to investigate biological and potential behavioral factors related to CVD. Participants were recruited from Framingham, Massachusetts and was recognized as a sample without widely generalizable characteristics. The area was chosen because if its adequate population, compact area for convenience, stable population, proximity to a medical center, and other factors that was conducive for a long-term epidemiological study (D'Agostino, 1989).

The second generation of participants, comprised of offspring from the first cohort, was established in 1971, and new participants were added to reflect changing demographic characteristics of the community in 1994, known as the Omni 1 cohort. At the time of data procurement from NHLBI, 9 clinical exams of the offspring cohort and 4 exams from the Omni 1 cohort were included. Because dietary data were only available for the offspring cohort, and only available for 3 timepoints, these were the included timepoints in this analysis. The timepoints used for this analysis were times 5 (1991-1995), 7 (1998-2001), and 8 (2005-2008). The exam schedule for the participants was one exam every 4 to 6 years and the mean age at Time 5 was 55 years. The total sample for the offspring cohort at Time 1 was 5,124, and the sample utilized in the timepoints specified in the current study totaled 4,004 participants.

Current Study

Number of variables collected. The study collected many biological markers in order to track the prevalence of CVD as well as test the efficacy of the diagnostic procedures available. Risk behavior hypotheses were also included in the main study, in the hopes of uncovering their association with the development of CVD and tracked smoking, alcohol use, dietary intake, and physical activity variables alongside the biological markers for diagnostic purposes. For the purposes of the current study, behavioral data related specifically to the use of alcohol and tobacco, as well as physical activity and fruit and vegetable intake.

Variables of interest

Smoking. Smoking is measured in the FHS utilizing direct, retroactive, self-report questioning regarding smoking use. The study assessed for history as well as current use, though did not ask about plans to quit smoking for those who were. For the purposes of the current analyses, smoking will be treated in analysis as dichotomous (smoking or non-smoking).

Alcohol use. Much like smoking, alcohol use in the FHS was measured utilizing specific, retroactive, self-report questioning about specific types of alcohol. The FHS assessed specific types of alcohol, including beer, wine, and liquor. For the current study, these types of alcohol were combined and assessed as an alcoholic drink rather than a specific type (average daily alcohol use). Alcohol use data will be treated as dichotomous such that an individual did or did not exceed 2 drinks per day for men or 1 drink per day for women (United States Dietary Guidelines Advisory Committee, 2010).

Physical activity. The FHS utilized a specific activity interview measuring many aspects of physical activity. The FHS also assessed for difficulty in activities of daily living, which may contribute to sedentary or physical activity behaviors. For the purposes of continuity and generalizability, the current study utilized measures of weekly physical activity. Physical activity will be reflected as dichotomous by either meeting or not meeting minimum recommended activity levels for adults ((USDHHS, 2008). It is worth noting that while the current analysis will utilize these recommendations, physical activity recommendations have changed throughout the lifetimes of the participants in the study. The first official guidelines for physical activity were not issued by the USDHHS until 2008 and general as well as cultural expectations for physical activity were previously inconsistent.

Dietary intake. In the FHS, dietary intake was measured using the Food Frequency Questionnaire (FFQ; Willett et al., 1985). The FFS is a detailed, self-report measure assessing the average amount of specific foods an individual consumes. Because the data were available through the FFQ, the categories of fruits and vegetables were collapsed and combined into a representative FV variable (average daily fruit and vegetable intake). Fruit and vegetable intake will be represented as dichotomous such that a person either did or did not meet the minimum federal recommended amount of FV.

Moderating variables. Waist to height ratio was calculated using height and waist measurements which were collected in regular check-ups for data collection in the study. The cut-offs for risk categorization were adapted from previous research, including low-risk (<.50), moderate-risk (.50-.60), and high risk (>.6) categories. (Ashwell & Gibson, 2019). Gender in the study is dichotomous (men and women) as the FHS study did not include categories for other gender identities. Age was collected at the onset of participation in the study and calculated based on the dates of the data collection timepoints.

Outcomes

Behavior cluster. The main outcome variable for this analysis was the type/pattern of health risk behaviors (i.e., latent class) each person fell into at each time point. The analyses will be aimed at identifying different types of health risk behaviors (i.e., latent classes) and tracking the stability of or transition among these classes over time. Moderating variables of waist to height ratio, gender, and age will also be used to examine group differences in class membership as well as patterns of transition between classes over time and class stability relative to group membership.

Data analysis

Latent transition analysis (LTA) was conducted using PROC LTA in SAS (Lanza, Dziak, Huang,Xu, & Collins, 2011). Because PROC LTA uses full information maximum likelihood (FIML) to address missing data, the entire sample was included to identify health behavior classes and their transitions over time, assuming data were missing at random. To determine the optimal number of latent health risk behavior classes, relative fit indices (Akaike's information criterion, AIC; Bayesian information criterion, BIC), model parsimony, and interpretation were utilized (Lanza, Bray, & Collins, 2013). In order to identify homogeneous subgroups based on the samples' health behaviors, a latent class analysis (LCA) was conducted using PROC LCA at time 1. LCA uses categorical data, which were calculated using CDC and AHA recommendations for health behaviors. In an unconditional model, latent class models estimate each person's probability of falling into each latent class to determine his/her latent class membership. Model identification was confirmed by examination of models using multiple starting values. Since the number of latent classes is unknown, multiple models were fit with differing numbers of latent classes. Bayesian information criterion were utilized to identify the most appropriate number of latent classes based on fit at time 1 (Tein, Coze, & Cham, 2013). After class identification at time 1, latent class structure was tested at times 2 and 3 to ensure measurement stability across times.

Once latent class structure was identified for all timepoints, the LTA was used to identify proportion of sample membership in classes at each time point as well as establish likelihood of individual movement from one class to another between timepoints. The LTA model has three sets of parameters. To answer the research question, "What are the types/classes of health behavior?" rho parameters (ρ) were examined, which indicate the probability of a positive response to each of the four behavior indicators by latent status and by time; for example, $\rho = 0.91$ for physical activity and Class 1 suggests that individuals categorized into Class 1 had a 91% probability of endorsing "yes" for physical activity (i.e., meeting the minimum weekly recommended requirement for physical activity). These parameters characterize the overall behavior profile for each health behavior class based on the four indicators. To answer the research question, “What are the proportions of participants in each class?” delta parameters (δ) were examined, which supply information about the size each health behavior class by providing the probable portion in each health behavior cluster for each timepoint. Lastly, tau parameters (τ) were utilized to answer the question, “How are the participants changing between each assessment?” This parameter indicates the probability of transitioning from one latent status at time t to another latent status at the following assessment (t+1). The tau parameters provide information about the stability of different health behavior clusters over time as well as to which cluster participants are likely to transition. Because LTA also allows for covariates, sex, age, and waist to height ratio (Yoo, 2016) were included into model as covariates for membership in health behavior clusters at time 1. The likelihood ratio test (LRT) statistic was used to compare the fit of models with and without each covariate. Multinomial logistic regression was used to assess how each covariate predicted T1 membership, relative to a reference class, by providing logit coefficients and odds ratios (ORs). Using LTA also allows for covariates to be used to predict cluster transition probabilities, but this model did not converge and could not be interpreted due to data sparseness. The data were also modeled using the grouping command in PROC LTA to explore how proportions and transition likelihoods may differ between sex, age groups, and key waist to height cutoffs (Gibson & Ashwell, 2020) Because health behavior clusters were found to be consistent at each time point using PROC LCA, measurement invariance was assumed across timepoints.

CHAPTER 4

Results

Secondary data from the Framingham heart study was utilized for analysis. The sample consisted of 4,004 participants (53.14% women, 99.22% white) who were administered measures of all 4 health risk behaviors at least once over the 3 selected time points. The mean age of the sample at time 1 is 54.8 (*SD* = 9.9), while at time 3 it is 66.8 (*SD* = 9.2). The average waist to height ratio for the sample at time 1 was 0.553 (*SD* = 0.08), indicating that the average participant fell into the “at risk” category of waist to height ratio (0.50; Lee, Lee, Lee, Kim, 2016). At Time 1, 24.22% of the sample fell into the “low risk” WHtR category, 52.57% were in the “moderate risk” category, and 23.21% were in the “high risk” category. By Time 3, those numbers had changed to 7.82%, 39.85%, and 52.33%, respectively, indicating that the sample skewed towards a higher WHtR as time progressed. At time 1, the overall average time participants spent engaged in heavy physical activity was .79 hours per day (*SD* = 1.38), with 57.61% meeting the weekly physical activity guidelines. The average amount of fruits and vegetables consumed per week was 5.48 (*SD* = 2.94) and 49.87% met guidelines for weekly fruit and vegetable consumption. Those who smoked any cigarettes at the time of assessment made up 18.11% of the sample and those who exceeded the recommended weekly amount of alcohol were 16.15% of the sample.

Overall changes in health risk behavior indicated a mix of trajectories over the course of the study (Figure 1, Table 3). Smoking decreased overall in the sample with 18 percent of the sample smoking at Time 1 and less than 10 percent smoking at time 3, with the biggest reduction in smoking coming between times 1 and 2. Alcohol use stayed consistent overall in the sample with the range over all times falling between 15-18 percent. Physical activity varied widely between time points, increasing between Time 1 and Time 2 and returning slightly below Time 1 levels at Time 3. Proportion of fruit and vegetable intake increased slightly at each time point but remained generally consistent over time. Average waist to height ratio increased sharply from Time 1 to Time 2 and continued to increase from Time 2 to Time 3 (Figure 2).

Latent Class Analysis. For latent status identification, the LCA was run using models of 2, 3, 4, and 5 latent statuses for maximum fit and parsimony. Based on the likelihood-ratio G^2 statistic, degrees of freedom, AIC and BIC for each model (Table 2), 3 cluster model appears to represent the data best. After examination, the 3 cluster model was interpretable and in line with prior research (Noble, Paul, Turon & Oldmeadow, 2015).

Will health risk behaviors show consistent, homogenous clusters?

The item response probabilities suggest these interpretable labels for the 3 latent statuses: "unhealthy," "healthy," and "low energy balance." As Table 3 shows, the unhealhty health behavior cluster represented about 12.69% of the sample and showed an increased likelihood of falling short of the behavior recommendations for all 4 of the health risk behaviors compared to the other clusters (Table 4). Most notably, the unhealthy cluster had a 0% chance of reporting no cigarette use, indicating that the majority of the sample's smokers were in the high risk cluster of health behaviors. Conversely, the healthy behavior cluster had an increased likelihood of meeting weekly guidelines for all 4 health risk behaviors (55.6% or better). In the low energy balance health behavior cluster, almost all members met guidelines for cigarette and alcohol use

(93.13% and 86.35%, respectively) but a high percentage did not meet guidelines for physical activity and fruit and vegetable intake (99.91% and 53.69%, respectively). Notably, the healthy cluster showed a lower rate of meeting guidelines for alcohol use than the low energy balance cluster (82.77% and 86.35%, respectively) and the unhealthy category showed the lowest rate of meeting guidelines for alcohol use (71.61%). The unhealthy cluster showed the lowest rates of fruit and vegetable consumption with only 24.82% of the cluster meeting the recommended levels (pictured in Figure 3).

Will the latent clusters of behavior appear across the time series? How does membership change in these clusters across time?

Latent clusters of behavior existed at each time point and the proportions of the sample present in each cluster are shown in Table 3 and Figure 4. The stability of membership in the clusters and the patterns of transition were examined and are displayed in Table 5 and Figure 5. The entries along the diagonal of each transition probability matrix (marked in bold font in Table 5) reflect the probability of membership in the same latent status at two consecutive times of measurement. For example, individuals in the healthy cluster at Time 1 were likely to remain in the healthy cluster at Time 2 (65.9%). Individuals in the unhealthy cluster at Time 1 were unlikely to remain in the unhealthy cluster of behaviors at time 2 (7.8%). Likewise, individuals in the unhealthy cluster at time 2 were unlikely to remain in the unhealthy cluster at time 3 (5.4%). In the healthy cluster, individuals were likely to maintain their cluster status between times one and two (65.9%), but were less likely to maintain their status from time two to time three (37.4%). Those in Low Energy Balance cluster were not likely to stay in their cluster from time one to time two (27.6%), but were likely to maintain their cluster status from time two to time three (58.0%).

Entries off the diagonal of each matrix reflect the probability of transitioning to a different status at the next timepoint. From Time 1 to Time 2, the most common cluster to transition into was the Healthy cluster. Notably, of individuals in the unhealthy cluster at Time 1, 63.22% transitioned to the healthy cluster and 29% transitioned to the low energy balance cluster at Time 2. Conversely, a small portion of those in the healthy cluster at Time 1 transitioned to the unhealthy cluster at Time 2 (6.22%). Overall, the participants were least likely to transition to the unhealthy cluster and most often transitioned to the healthy cluster at Time 2 and the Low Energy Balance cluster at Time 3.

Do demographic characteristics moderate membership in behavior clusters as well as transition probabilities between clusters over time?

Gender. Several grouping variables were added to the 3-status model to compare the prevalence and transition of each latent cluster for men and women. Tables 7 and 8 show the prevalence of each latent cluster at each time point for men and women, respectively (pictured in Figure 6 and 7). Gender was a significant predictor of class membership at time one ($p < 0.05$) Notable differences in cluster membership were noted at Time 1, with women more likely to belong to the low energy balance cluster than men (62.5% women versus 38.3% men) and men more likely to belong to the healthy status (49% men versus 25.9% women). There were no notable differences in prevalence within clusters between genders for Time 2 or Time 3.

Tables 9 and 10 illustrate the transition probabilities for men and women, respectively. The transition patterns for men and women were generally similar from

Time 1 to Time 2 as well as Time 2 to Time 3. One notable difference was found in the first transition where men had a higher likelihood of staying in the unhealthy cluster than women (12.34% versus 2.84%). Some notable differences in the second transition included women being more likely to transition from unhealthy to low energy balance (62.58% versus 53.59%) and more likely to move from low energy balance to healthy (43.21% versus 36.97%).

Waist to height ratio. Tables 11, 12, and 13 show the prevalence of each latent cluster at each time point for different risk levels of waist to height ratio at Time 1 (pictured in figures 9, 10, and 11). Waist to height ratio was not a significant predictor of class membership at Time 1 ($p > 0.05$). Notable differences in cluster membership were observed at Time 2 and Time 3, with Time 1 showing consistent membership across groups. At Time 2, individuals in the "low risk" category of WHtR were twice as likely (4.18% versus 8.73%) to be in the unhealthy cluster when compared to the "high risk" WHtR group. Also at Time 2, the "low risk" and "moderate risk" WHtR groups were more likely to be in the healthy cluster of behavior when compared to the "high risk" WHtR group (69.58% and 65.97% versus 55.71%), while individuals in the "high risk" WHtR group were more likely to be in the low energy balance cluster (40.11% versus 27.91% "moderate risk" and 21.69% "low risk"). No notable differences were observed between WHtR groups at Time 3.

Tables 14, 15, and 16 illustrate the transition probabilities for different WHtR risk categories (pictured in figures. The "low risk" and "moderate risk" groups had generally similar transition patterns. From Time 1 to Time 2, participants were most likely to transition to (or stay in) the healthy cluster, but the unhealthy cluster was more stable when compared to the overall sample (9.2% versus 7.77%). For individuals in the "high risk" group, the unhealthy cluster was very unlikely to remain stable (1.93%) but individuals were more likely to transition to the Low Energy Balance group than individuals in the "low" or "moderate" risk groups. Most notably, individuals in the "high risk" group saw the highest stability in the unhealthy cluster in the transition from Time 2 to Time 3 (29.17%), far exceeding the trend in the overall sample for the second transition (5.4%). This also meant that individuals in the unhealthy cluster had a much lower likelihood of transitioning into healthy or Low Energy Balance clusters when compared to "low" or "moderate" risk groups. Stability of clusters for the "high risk" WHtR group are pictured in Figure 8.

Age. Tables 17 and 18 show the prevalence of each latent status at each time point for participants who were younger and older than 55 at Time 1, respectively (pictured in Figures 12 and 13, respectively). Age was a significant predictor of class membership at Time 1 ($p < 0.05$). Notable differences in cluster membership were observed at Time 1. Younger participants were much more likely to belong to the unhealthy cluster than older participants (17.58% younger versus 6.7% older), but younger participants were more likely to belong to the healthy cluster (40.05% versus 32.09%). Furthermore, older participants were more likely to be in the Low Energy Balance cluster at Time 1 (61.21%) than younger participants (42.37%). There were no notable differences in prevalence within clusters between age categories for Time 2 or Time 3. Tables 19 and 20 illustrate the transition probabilities for younger and older participants, respectively. The most notable difference in transition patterns occurred from Time 1 to Time 2 in the unhealthy cluster. The older participants were much more likely to stay in the unhealthy cluster than younger participants (17.22% versus 5.57%, respectively). From Time 2 to Time 3, the pattern flipped and younger participants were more likely to stay in the unhealthy cluster (8.4% versus 2.99%). Overall, individuals were most likely to transition to the healthy cluster after Time 1 and the Low Energy Balance cluster after Time 2.

CHAPTER 5

Discussion

Using a data sample collected over a three timepoints the current study found that health risk behaviors such as smoking, alcohol misuse, physical inactivity, and insufficient fruit and vegetable intake cluster and the stability of these clusters changes over time. These clusters are consistent with previous research (Noble, Paul, Turon & Oldmeadow, 2015) and included three classes: an unhealthy class, a healthy class, and a low energy balance class. Though these classes align with prior literature in many ways, they divert in some important facets. Previous research has demonstrated a relationship between addictive behaviors and energy balance behaviors, which was not present in the current study (Noble, Paul, Turon & Oldmeadow, 2015). Though the "low energy balance" class had lower likelihoods of meeting both physical activity and fruit and vegetable guidelines when compared to the healthy class, the class was highlighted most by the very high likelihood that individuals in this class would not meet the physical activity guidelines. This class had the least likelihood of meeting physical activity guidelines, including the "unhealthy" class.

The decoupling of energy balance behaviors in the current sample may be impacted by the age of the sample at the timepoints used in the study, as physical activity levels tend to decrease in older adults as barriers to physical activity increases (White, Wojcicki, & McAuley, 2012). When considering the age of the sample, it may also be important for conceptualizing other reasons why physical activity may have presented in this way. Behaviors like smoking, limited excessive alcohol use, and fruit and vegetable intake may be most impactful in maintaining health in older age, while physical activity benchmarks may not be achievable as more physical limitations are present. As the sample ages, it may be possible that *any* physical activity can be useful in maintaining a healthy lifestyle rather than physical activity benchmarks, but the other guidelines may continue to apply.

The proportion of participants in the unhealthy class decreased over time and consistently included the fewest participants throughout the study. From time 1 to time 2, participants in the "unhealthy" class were most likely to move to the "healthy" class rather than the "low energy balance class". It is rather unexpected that participants would have changed multiple behaviors and transitioned from having all four HRB to having zero. Though it may seem that health behavior change happened all at once for these participants, it is important to consider that between time 1 and time 2 about 10 years had passed, during which time each behavior could have had its own short-term trajectory. One potential factor in the transition to "healthy" rather than "low energy balance" may be the overall health impact of smoking, since the vast majority of smokers were found in the "unhealthy" cluster. Research has shown that overweight smokers interested in quitting are also interested in losing weight or changing energy balance behaviors (Wee et al., 2001). Since alcohol consumption between the healthy and unhealthy clusters was not extremely different (18% versus 29%, respectively), impact on both energy balance behaviors likely would have swung participants into the "healthy" cluster, particularly if they increased physical activity as well. This suggest that, when people are shifting into the action stage of behavior change on one HRB such as smoking, it may translate to changes in both energy balance behaviors rather than one or the other (Paiva et al., 2012). This aligns with findings from coaction and multiple behavior change research (Johnson et al., 2008; Mauriello et al., 2010; Prochaska et al., 2004, 2005). One other important consideration for the transitions in group membership from “unhealthy” to “healthy” were changing health behavior norms within the sample at the time. Measures were being taken by the federal government to impose taxes and overall stigmatization for smokers and was making concerted efforts to inform people of healthy guidelines for physical activity and dietary intake. These cultural shifts in expectations for health behavior may have had a broad impact on the transitions of health behavior for this cohort over such a long time period. From time 2 to time 3, participants in the “unhealthy” class were most likely to transition to the “low energy balance” class. The average age of participants at time 3 was 66.8 years, showing a significant shift into older age for a large portion of the sample. This suggests that, as individuals age, addictive health behaviors may be prioritized in health behavior change strategies and energy balance behaviors may be more difficult to change. Data suggests individuals above age 65 have the most success quitting smoking but are least likely to adopt physical activity (Sachs-Ericsson, Schmidt, Zvolensky, Mitchell, Collins, Blazer, 2009; White, Wojcicki, & McAuley, 2012)

The proportion of individuals in the healthy class fluctuated. Time 2 saw the highest proportion of participants before losing them once again by Time 3. Transition probabilities indicated that participants from each class at Time 1 were most likely to transition to the healthy class at Time 2. This trend changed from Time 2 to Time 3, where participants from each class were most likely to transition to the “low energy balance” class. This pattern of proportions and transition suggests that individuals may be motivated and able to attend to multiple health risk behaviors initially and perhaps for an extended period of time but their ability to maintain all 4 healthy behaviors long-term may be impacted by barriers such as time, lack of enjoyment, low socioeconomic status, or other individual barriers (Kelly, Martin, Kuhn, Cowan, Brayne, & Lafortune, 2016). The behaviors most likely to be affected by this trend are energy balance behaviors. These findings may indicate that addictive behaviors are more likely to be avoided when quit but energy balance behaviors are more likely to fluctuate due to the necessity of *modulating* rather than simply *avoiding* the behaviors.

The proportion of participants in the “low energy balance” class fluctuated over time but had the highest proportion of the sample at both Timepoints 1 and 3. Because the “low energy balance” cluster had the lowest incidence of physical activity, fluctuations in membership in this cluster may be related to changes in physical activity levels while maintaining levels of addictive behaviors. This pattern is supported by transition in and out of the “healthy” cluster overall by participants. Participants in the “low energy balance” class were most likely to transition to the “healthy” class at time 2, but the class was relatively stable between Times 2 and 3, while all participants were most likely to transition to the “low energy balance” class between Times 2 and 3. This pattern indicates that individuals who were already able to avoid addictive behaviors may have addressed energy balance behaviors between Times 1 and 2, and may have specifically showed changes in physical activity levels. However, due to the difficulty of maintaining energy balance behaviors over time and barriers impacting physical activity, participants may have transitioned back to the “low energy balance” class between Times 2 and 3. Because changes in physical activity may be driving the shift from the “healthy” class to the “low energy balance” class, it is important to consider how the age of the sample may be impacting the transitions in health behaviors over time (Atella et al., 2019; Costello, Kafchinski, Vrazel, & Sullivan, 2011).

The unhealthy class was the least stable of the classes and had a significantly lower proportion of the population. Even though most of the sample was in the “healthy” cluster at time 2, the average WHtR for the entire sample continued to rise across all timepoints. This suggests that increasing healthy energy balance behaviors like physical activity and fruit and vegetable intake is inversely correlated with WHtR in this sample, which aligns with research suggesting that biological processes generally favor weight gain as opposed to long-term weight loss (Hill, Wyatt, & Peters, 2012). Furthermore, due to the fluctuation of physical activity in particular in the sample, it may be a signal of the long-term effects of yo-yo dieting and the impacts of discouragement due to frustrating results (Mehta, Smith Jr, Muhammad, & Casazza, 2014). Over time, cluster proportions shifted from low energy balance to healthy, back to low energy balance across timepoints, with the unhealthy group showing consistent reduction throughout the study.

Men and women tend to present in these clusters differently, aligning with previous research on presentations of health behavior in men and women (Blanck, Gillespie, Kimmons, Seymour, & Serdula, 2008; Thompson, Yaroch, et. al., 2011; Caspersen, Pereira, and Curran, 2000; Hickey and Mason, 2017; King, Dube, Tynan, 2012; Wilsnack, Wilsnack, Kristjanson, Vogeltanz-Holm, and Gmel, 2009). Gender was a significant predicter of class membership at time 1. These results indicate that, compared to women, men had a higher likelihood of membership in the healthy cluster at Time 1 than women. Women were more likely to be in the low energy balance cluster at time one. From time 1 to time 2, men were more likely to stay in the unhealthy cluster than were women. From time 2 to 3, women in the low energy balance class at time 2 were more likely to stay in the low energy balance class at time three, while men were more likely to transition from the low energy balance class into the healthy class. These findings suggest that men and women may participate and change their energy balance behaviors differently, aligning with previous research (Blanck, Gillespie, Kimmons, Seymour, & Serdula, 2008; Thompson, Yaroch, et. al., 2011). Importantly, physical activity in the current study was not limited to exercise. Consistent with general trends in the labor workforce, the men the sample were more likely to be employed in jobs that required more physical labor than women. Furthermore, prior studies suggest that women are more likely to consume more fruits and vegetables than men (Wardle et al., 2000b). Because exercise behavior was so low in the low energy balance class, this increased consumption of fruits and vegetables by women may explain their likelihood of transitioning from the unhealthy class to the low-energy balance class.

The transition probabilities when grouped by WHtR were similar to that of the overall sample. WHtR was *not* a significant predictor of health behavior class at time 1. These results indicate that individuals' WHtR was not a good predictor of membership in any of the health risk behavior clusters at time 1. This aligns with previous research suggesting that individuals with obesity are likely to have engaged in or even are currently engaged in efforts to change their dietary and physical activity habits (Yaemsiri, Slining, & Agarwal, 2011; Serdula, Mokdad, Williamson, Galuska, Mendlein, & Heath, 1999). Health behavior change recommendations solely in response to WHtR may not be a meaningful intervention chronic disease management or prevention in the form of weight management, especially since even participation in weight control efforts like physical activity often do not lead to a reduction in weight and outcomes based solely on weight loss may not see progress (Caudwell, Hopkins, King, Stubbs, & Blundell, 2009). This strategy for recommendations may also lead to increased stigma, resulting in less engagement with the healthcare system and overall negative experiences with health behavior change (Polivy & Herman, 2002; Prochaska, & Levesque, 2002). Health risk behavior patterns should be taken into account for all patients, regardless of WHtR risk status.

Proportions between the "unhealthy" and "low energy balance" groups fluctuated less compared to the low and moderate risk WHtR categories as well as compared to the overall model. The group that had the highest stability of unhealthy behaviors was the high risk WHtR group from Time 2 to Time 3 at 29%. The "unhealthy" class showed the lowest proportion at each timepoint and only represented 4% of the sample by Time 2, but its stability was still notable when compared to the overall model (5.4%) or any other groups (<9%). The low-risk WHtR group showed only a 0.4% chance of staying in the unhealthy class between Times 2 and 3. This suggests that being in the high-risk WHtR class may not only impact energy balance behaviors, but addictive behaviors as well, especially as individuals age. This may be impacted by poor impressions of their own health and lack of efficacy in changing their health status (Okosun, Choi, Matamoros, & Dever, 2001). These results also indicate that individuals participate and change their health risk behaviors regardless of their WHtR status, but barriers like pain, discomfort, and dissatisfaction with results may impact changes as individuals age (Eagan, Mahmood, Fenton, Redziniak, Kyaw Tun, Sreenan, McDermott, 2013). Furthermore, factors *outside* of health risk behavior may have a greater impact on WHtR as well as risks associated with WHtR status.

It is important to note that the age of the sample was more concentrated in later adulthood by time 1 and by time 3, the average age of the sample was over 65 years of age. This picture of middle-age transitioning to older-age is important but findings are unlikely to generalize to capture health behavior for young adults transitioning into middle age. The participants presented in the clusters of health behavior differently at time 1 when grouped by age and age was a significant predictor of class membership at time 1. Participants who were under the age of 55 at time 1 were more likely to be in the "unhealthy" cluster of health behavior and were less likely to be in the "low energy balance" cluster of health behavior. These results may be indicative of the lack of health consequences of health risk behavior for younger individuals compared to older individuals (Sachs-Ericsson et al., 2009). Some health risk behavior change may be driven by avoiding negative acute health consequences rather than avoiding long-term negative health outcomes. As consequences increase in salience, health behavior change becomes more likely (Sachs-Ericsson, Schmidt, Zvolensky, Mitchell, Collins, Blazer, 2009). Between times 1 and 2, younger participants were more likely to stay in the "unhealthy" cluster of behaviors when compared to the overall model (17% compared to 5%, respectively). Another important note regarding the age of the sample is to understand how barriers to physical activity may affect an older population. Since physical activity was so sparse in the "low energy balance" cluster, it is possible that individuals were continuing to get *some* physical activity as they aged but were limited by physical and environmental barriers (Atella et al., 2019; Costello, Kafchinski, Vrazel,

& Sullivan, 2011). An appropriate adage for older individuals may be that "some is better than none" when it comes to physical activity, especially when limitations exist. The dichotomous and broad nature of the physical activity guidelines (USDHHS) may miss important exercise data that might explain the drop-off in physical activity within the sample over time.

When compared to overall trends of the sample, the transition data showed that the proportion of the population that engaged in health risk behavior shifted more than is represented by overall trends. Overall smoking rates decreased in the sample to rates that were comparable across a general older adult sample (8.15% and 9%, respectively) (Centers for Disease Control and Prevention, 2016). This would indicate that new smokers decreased over time and smokers were quitting. Due to high association with disease factors causing mortality, death rates in the sample may have been higher among long-term smokers. Combined with a lack of new smokers, this may partially explain the decrease in smoking rates over time in the sample. Alcohol use was generally consistent in the sample across time. This would indicate that the overall sample was not making changes to their alcohol consumption over time.

Physical activity varied across timepoints, indicating that it was a broadly adopted health behavior, but the changes were not resilient. Physical activity is impacted by a number of factors and can be difficult to maintain after initial adoption. Furthermore, physical activity tends to be impacted by age. The current sample's mean age of 66.8 at Time 3 would indicate that the sample would be impacted by age-related barriers and a decrease in physical activity is consistent with previous research (Atella et al., 2019; Costello, Kafchinski, Vrazel, & Sullivan, 2011). Fruit and vegetable intake over time was generally consistent with a small trend upwards over time. This indicates that, overall, the sample did not vary in their dietary habits over time. If single behaviors were assessed cross-sectionally, three of the 4 health behaviors would have changed very little over the course of the three timepoints. Latent transition analysis allows attention to individual participant changes in health behavior as well as impact of group membership on health behavior.

Important considerations for further study

Some factors are important for the understanding of health behaviors but were beyond the scope of the current study. Ambient factors, such as sleep, stress, and pain, impact all of the health risk behaviors discussed in the current study. In fact, increasing access and efficacy of treatments for sleep disturbance, stress and mental health concerns, and chronic pain will almost certainly also increase our ability to better treat specific health risk behaviors by decreasing barriers for successful treatment.

Sleep. Sleep can be affected by a wide variety of variables and disrupted sleep, likewise, can have wide-ranging effects. While sleep and chronic disease may not be directly linked, many behaviors associated with chronic diseases like type 2 diabetes and CVD can be altered by a lack of restful sleep. For example, as sleep is disrupted, motivation for physical activity can decrease due to general tiredness and sedentary behavior can, in turn, increase (Chaput & Dutil, 2016). With poor sleep comes disruptions in appetite that may be related to energy balance as well as alterations to the circadian rhythm (Borbély, 1982). As energy levels and appetite become more dysregulated, so follows the disruption of a sleep schedule. Poor sleep is associated with increases in added sugars and refined carbohydrates, decreases in physical activity, and increases in general stress (Chaput & Dutil, 2016). Conversely, reliance on caffeinated beverages like coffee and soda for energy after poor sleep can further dysregulates stimulation levels before bed as well as serve as extra sources of sugar (Keast, Swinburn, Sayompark, Whitelock, & Riddel, 2015). Because sleep plays a role in energy, appetite, and stress management, it can both be an important consequence of health-risk behaviors as well as an important component of altering health-risk behaviors.

Stress. Causes of stress can be wide-ranging and have a multitude of physical and psychological effects. Though the scope of the current study does not include data on indicators of stress, it is an important component of both disease processes and multiple health risk behaviors. Chronic and acute stress can play direct rolls in biological functions that affect the course of cardiovascular disease and other chronic diseases that can lead to poor treatment outcomes if stress is not appropriately managed (Lukens, Turkoglu, & Gurg, 2012). Specifically, anger-related stress is associated with worse outcomes in treatment and chronic disease due to such physiological factors (Chida & Steptoe, 2009).

Aside from the biological effects that stress can have on disease processes, managing stress can directly affect health risk behaviors due to poor coping skills and the use of behaviors like smoking, stress eating, alcohol use, and an increase in sedentary behavior to mitigate the effects of chronic or acute stress (Park & Iacocca, 2014). The resulting cycle of alleviating stress paired with health risk behaviors makes the process of behavior change even more difficult, especially if an individual does not feel they have the personal resources to cope with stress without them.

Pain. Pain is an important HRB variable due to its treatment complexity as well as its impact on several HRB. One study found that 38.5% of adults over the age of 65 experience some form of chronic pain, often hindering physical activity levels in a group of the population that sees a general decrease in physical activity (Larsson, Hansson, Sundquist, & Jakobsson, 2017). Individuals who experience chronic pain also use alcohol at a higher rate than the general population, since alcohol may be used as a way to mitigate chronic pain when other treatments are not effective (Von Korff, 2005). Chronic, untreated pain can also cause a marked increase in stress and cause strife in personal relationships, weakening the supports that may be needed for sustained health behavior change and risk aversion (Vachon-Presseau, 2018). Pain is an interesting example of how health risk behaviors may be related and cluster based on factors outside of each behavior on its own.

Physical environment

Social factors. Social and environmental factors are important aspects of all HRB changes. Seeking and maintaining social support are not only important parts of treatment success, it is also a skill that often needs to be learned in the realm of behavior change. Of any of the main risk behaviors, spending time with a social group that is not supportive or is actively impeding behavior change can completely derail the attempt, causing negative consequences not only due to the continued HRB, but also reinforcing the behavior due to experienced failure (Kwan, Bryan, & Sheeran, 2018). Pursuing and cultivating an environment that is supportive of one HRB may be able to translate to many.

Limitations

While the study had many strengths, it also included limitations. Firstly, because the data was utilized from the Framingham Heart Study without the inclusion of the OMNI participants, the sample was homogeneous and did not include a proportionate sample of individuals from multicultural backgrounds. The sample was almost exclusively white and utilized a convenience sample comprised of a large number of participants from the town of Framingham, Massachusetts, therefore the generalizability is limited. As throughout the paper, the age of the sample provides limited generalizability to changes in HRB starting at young-adulthood or adolescence. Thought the data provide a useful look into an aging population, it also may not encompass the changing attitudes and understanding of physical activity recommendations, dietary recommendations, smoking behaviors, or even government guidelines delineating problematic alcohol use. Though longitudinal data are useful in avoiding reliance on cross-sectional assumptions of generalizability, the evolution of health risk behavior research was unfolding as the sample was in established adulthood and older age. Understanding health behavior in groups that continue to experience oppression within the LGBTQI+ community is an important part of providing effective interventions for the population. The dataset used for the current analyses utilized a gender-binary response, running counter to current best-practice in data-gathering techniques. The data analyzed to examine group differences in the groups available, but do not provide a complete picture of how dynamics of health risk behavior can affect groups experiencing oppression.

Aside from demographic limitations, measurement tools were inconsistent over the course of the study, particularly for energy balance behaviors. Fruit and vegetable intake was only available at certain time points, limiting the number of timepoints that could be used for analysis. Physical activity data was only available at certain time points and was measured in inconsistent ways, forcing limitations on time points available for analysis as well. Physical activity in the study was measured using “heavy physical activity” measure which was based on retroactive self-report rather than tracking data. These measures are not as specific and retroactive activity tracking can vary in its accuracy. Furthermore, the measurement of health behavior was adapted from a study rather than intentionally designed for best fit. The dichotomous nature of the health risk categorization also may not have captured nuances that could be important for understanding the clustering of health risk behavior but were necessary for LTA analysis.

Data sparseness also caused challenges for drawing conclusions from the data. LTA accounts for missing data but other analyses were not possible or useful because the results were invalid due to data sparseness. Measurement invariance also could not be established within the study, weakening the results of the LTA analyses. At no time point was there a “complete” dataset – since the data were pulled starting at the fifth examination and data were assumed to be missing at random, participants may have missed “time 1” and only had data for another timepoint.

Attrition and missing data. LCA and LTA utilize a method of accounting for randomly missing data in the dataset called full information maximum likelihood (FIML) (Lanza, Dziak, Huang,Xu, & Collins, 2011). Though this strategy can be a useful data analysis strategy for a dataset with random missing data, there is a question of whether it is appropriate in the current context when the very behaviors being studied (health risk behaviors) may contribute to one aspect of data-missingness (death). The dataset used for the current analysis included an aging population, one that was more likely to experience incidences of NCI as well as death as a result of NCI. Since the study was interested in the way that HRB changed over a period of time, it may have been the presence of HRB that impacted the NCI status and, therefore, the missingness of the data. Though studies have established the feasibility of FIML in accounting for attrition in longitudinal studies, methods for missing data regarding attrition due to death have not yet been agreed upon (Biering, Hjollund, and Fydenberg, 2015).

Conclusions

The current study emphasized the importance of accounting for the relationship between health risk behaviors when assessing for health risk behavior change. When developing treatment recommendations for chronic disease management or prevention, it is important to consider the effects that changing one health behavior can have on another. Individuals tend to make health behavior changes in a range of categories, and they can often happen in clusters. The current study highlighted the importance of accounting for both transitions into *and* out of health clusters of HRB. Providers hoping to impact health behavior for patients who have multiple health risk behaviors may emphasize the acute importance of making changes in addictive behaviors while taking a broader, more dynamic approach to addressing energy balance behaviors. An important takeaway from this study is the importance of understanding the barriers and challenges that present for different demographics. When grouped by gender, age, and obesity status, different patterns of transition emerged, highlighting the importance of person-centered care. For example, an important note from the current study is that waist-to-height ratio was *not* a good predictor of health risk behavior status. It is paramount for providers to manage their biases towards larger bodied individuals, focusing less on weight loss and more on how to foster healthy behavior change for any patient in need. For example, since obesity status affected transition out of an unhealthy cluster of behaviors when waist-to-height ratio is at "high risk" levels, it may be important to tailor treatment strategies targeted at particular barriers for that group of individuals. Next steps may be to help identify important factors in facilitating transition to a healthier cluster of behavior for individuals in the "high risk" category, rather than focusing on traditional methods that have not worked for those individuals in the past.

The current study was unable to incorporate the entirety of the lifespan in its sample. Future longitudinal studies may be able to utilize life-long data from individuals from varying backgrounds, allowing for the potential to identify individual factors that may contribute to both NCI status as well as HRB cluster transitions across the lifespan. Furthering our understanding of how behaviors tend to change together over time can calibrate the tools we use in preventative and treatment efforts in supporting patients attempting long-term behavior change. Conversely, continuing to utilize existing datasets can help illuminate how HRB have changed as understanding of health behavior change and the effects of HRB have improved, especially when compared across demographic groups. While the current study highlights important findings from the sample available, datasets with participants from more diverse backgrounds can help also identify system-level impacts on HRB and how they differ for different groups across time. The current study highlighted the notion that health risk behaviors cluster and membership in clusters transition in the absence of a particular intervention, but future studies may incorporate interventions to identify which health behavior changes may have the most impact on others throughout the lifespan, rather than simply during an intervention or at follow-up. Understanding the long-term effects of coaction in health behavior change can help identify important in-roads for prevention and intervention efforts in NCI. Including other important factors, such as measures of stress, sleep, and chronic pain, will also further our understanding of HRB over the lifespan. These three ambient factors can provide a clearer picture to barrier and contributing factors to *why* an individual may be struggling with behavior change and help to re-orient providers to these factors rather than relying on individual accountability and stigmatizing non-adherence as non-compliance in helping visits. As studies can continue to complete the picture of factors contributing to HRB, the more tailored and effective provider intervention and prevention efforts can become.

Figures

Figure 1. Single Health Behavior Trends

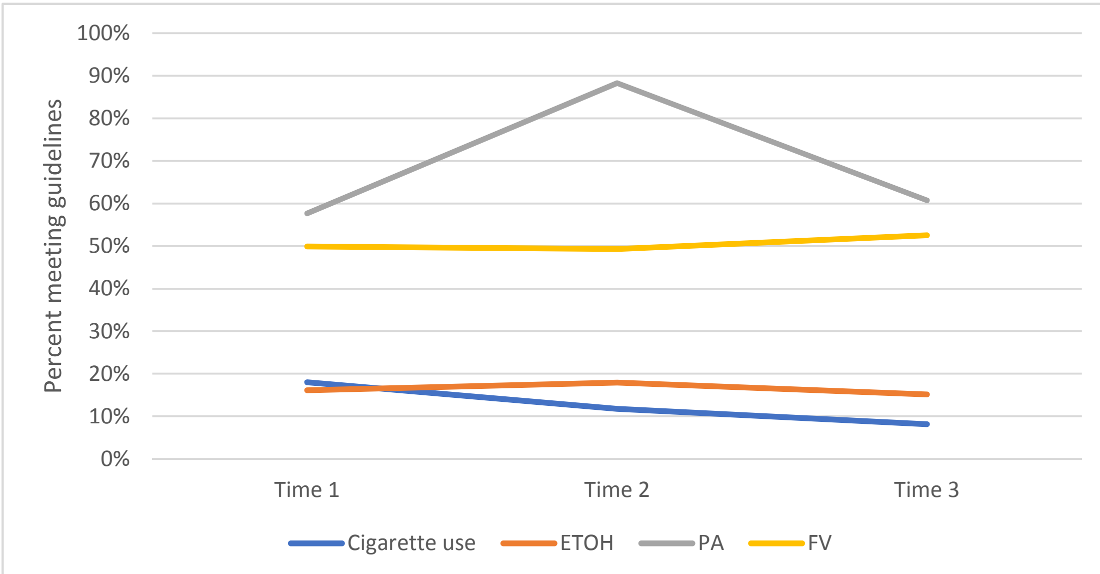


Figure 2. Waist to Height Ratio Trend

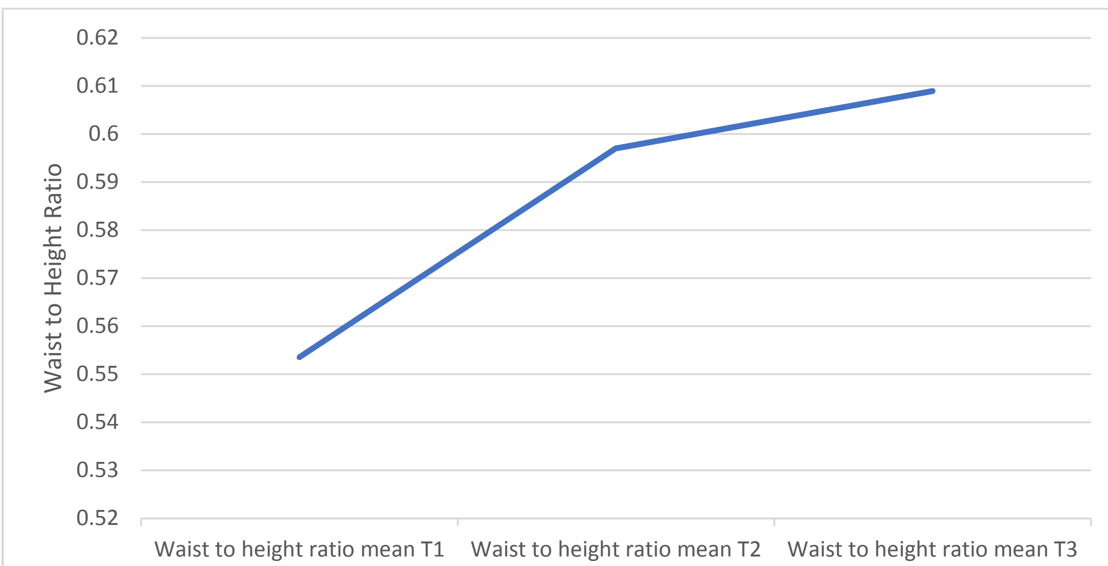


Figure 3. All Items Response Probabilities

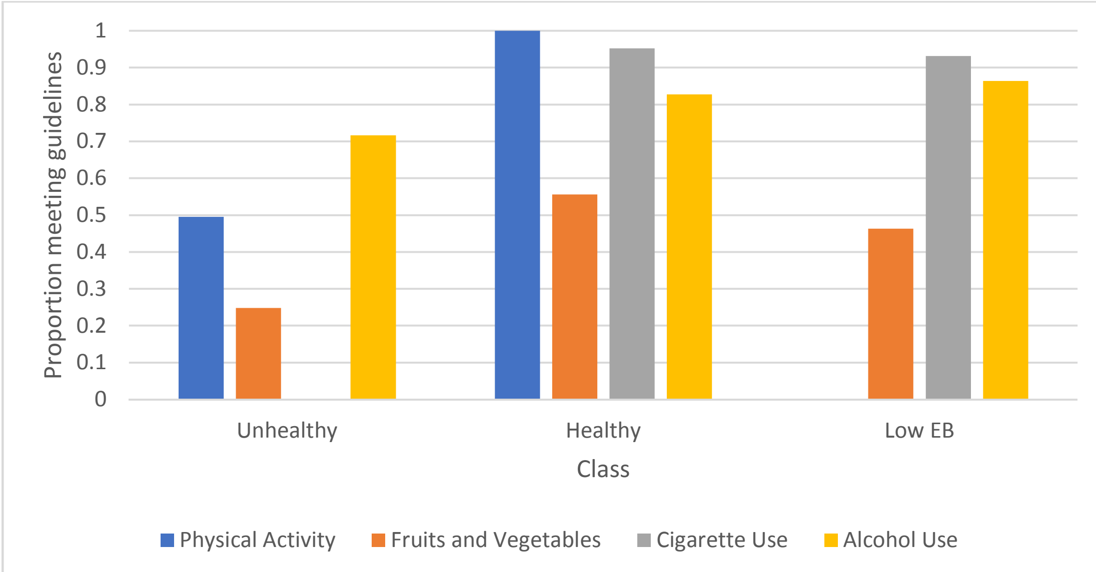


Figure 4. Class Membership Probabilities Trend

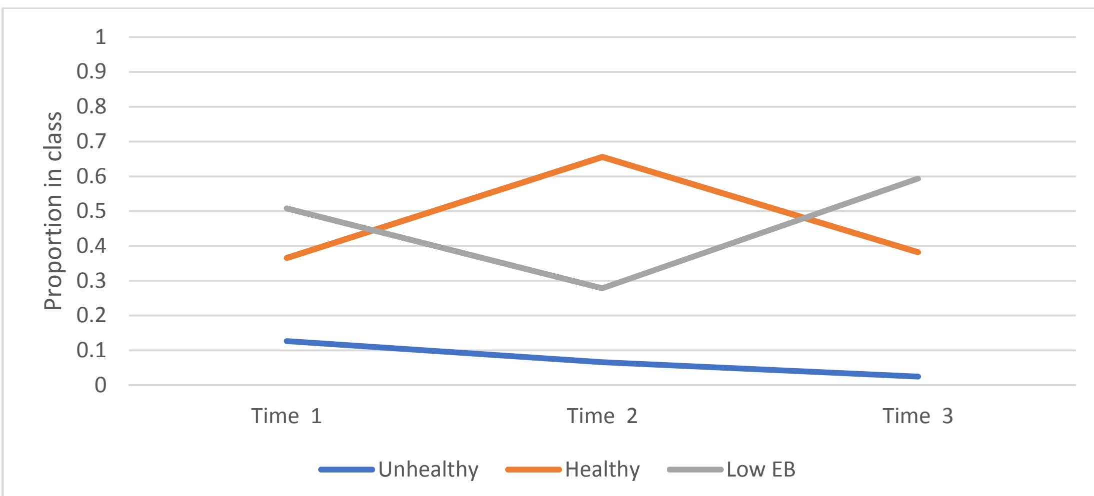


Figure 5. Latent Class Stability

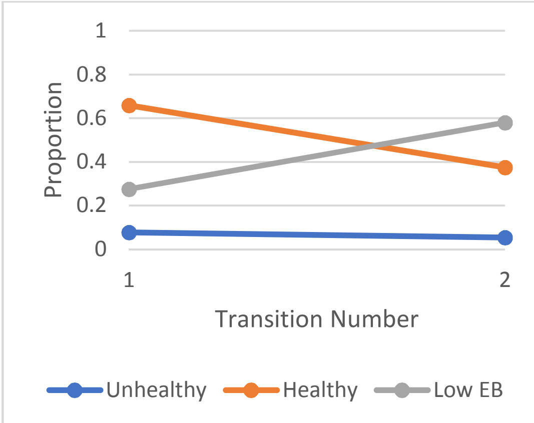


Figure 6. Class Membership Trend for Men

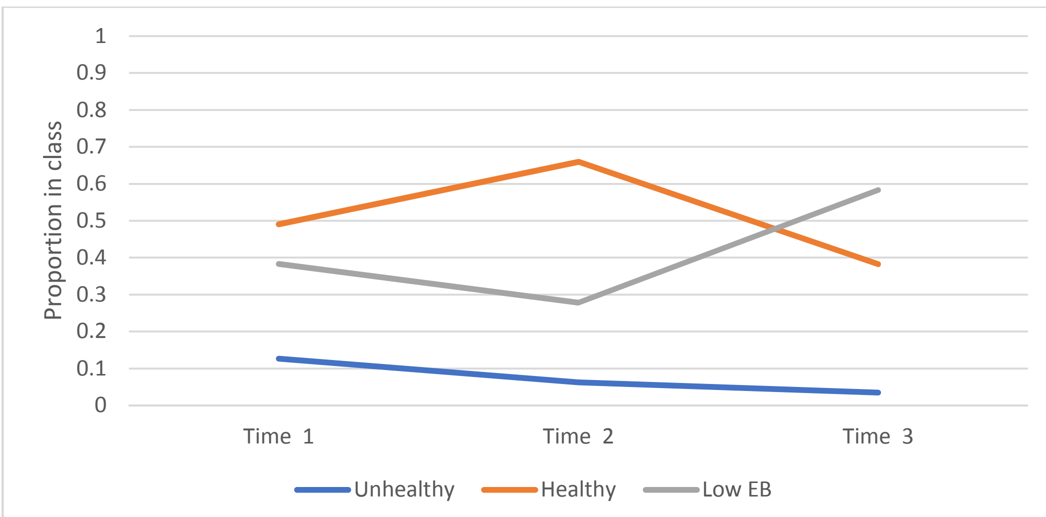


Figure 7. Classs Membership Trend for Women

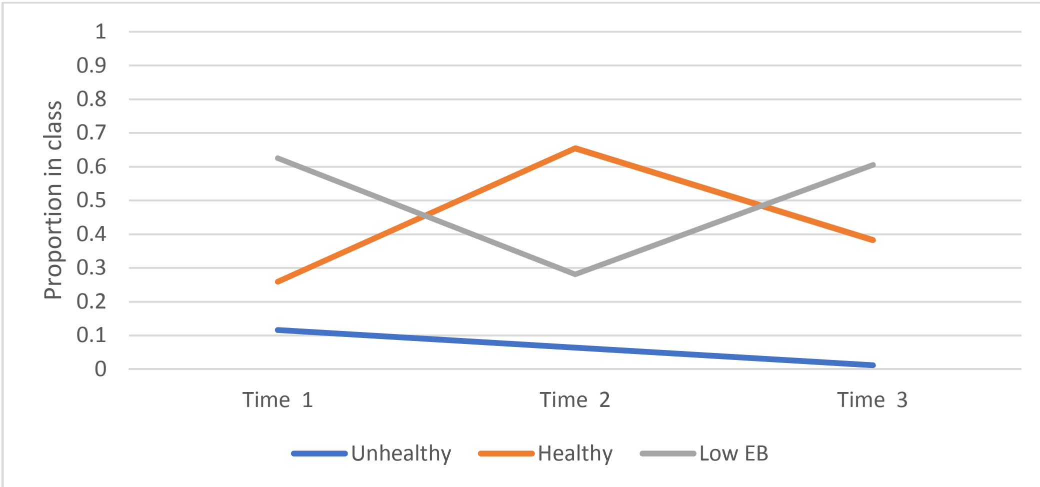


Figure 8. Stability of Latent Classes for High-Risk Waist-to-Height Ratio

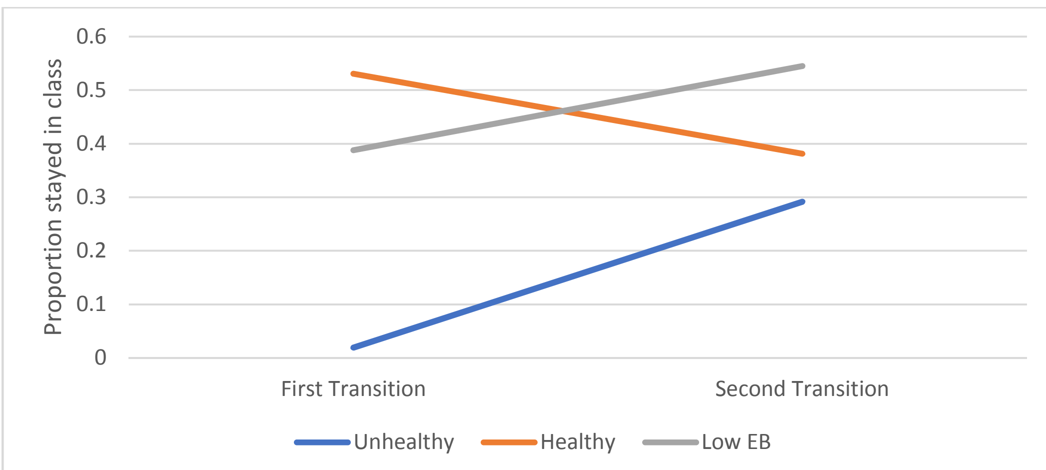


Figure 9. Classs Membership Trend for Low-Risk Waist-to-Height Ratio

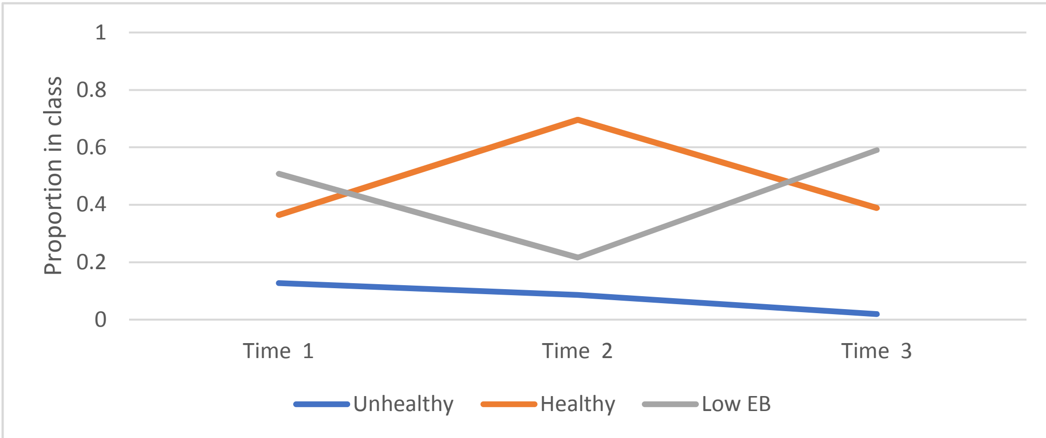


Figure 10. Classs Membership Trend for Moderate-Risk Waist-to-Height Ratio

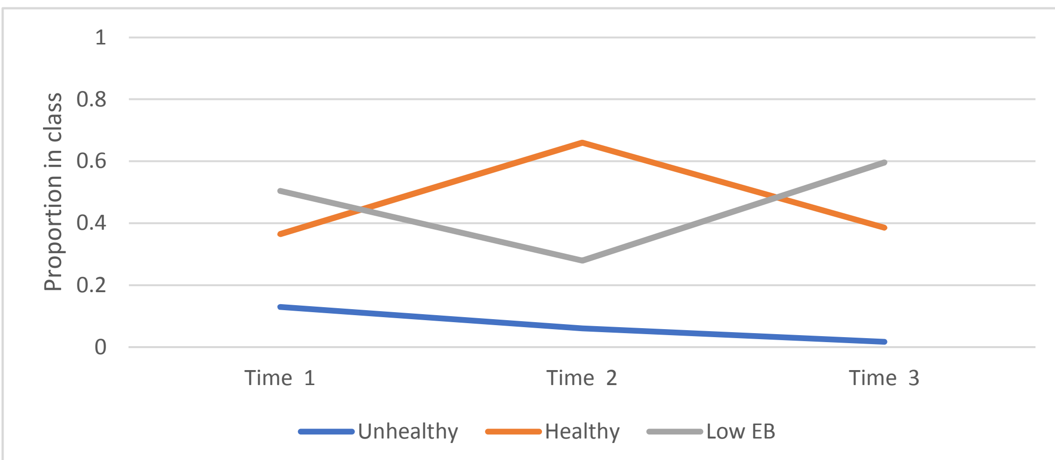


Figure 11. Classs Membership Trend for High-Risk Waist-to-Height Ratio

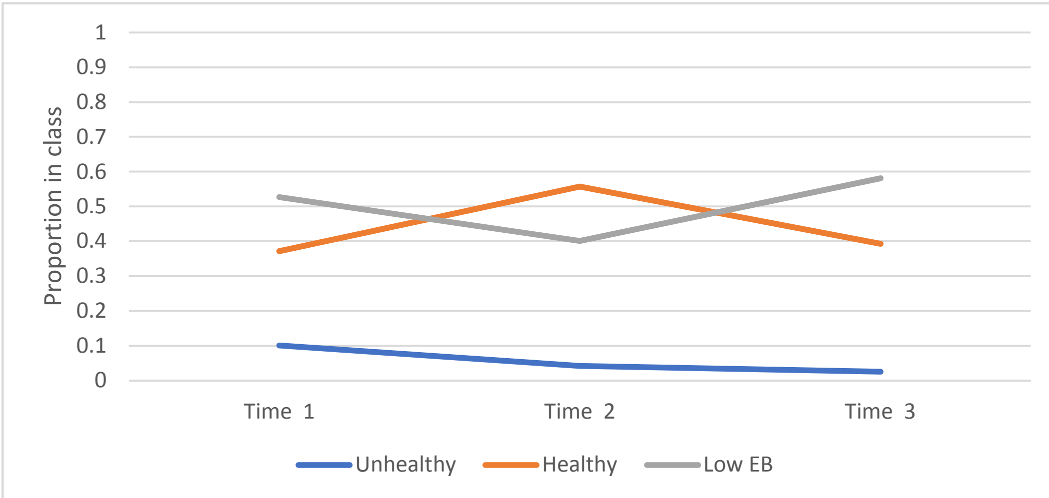


Figure 12. Classs Membership Trend for Younger Participants

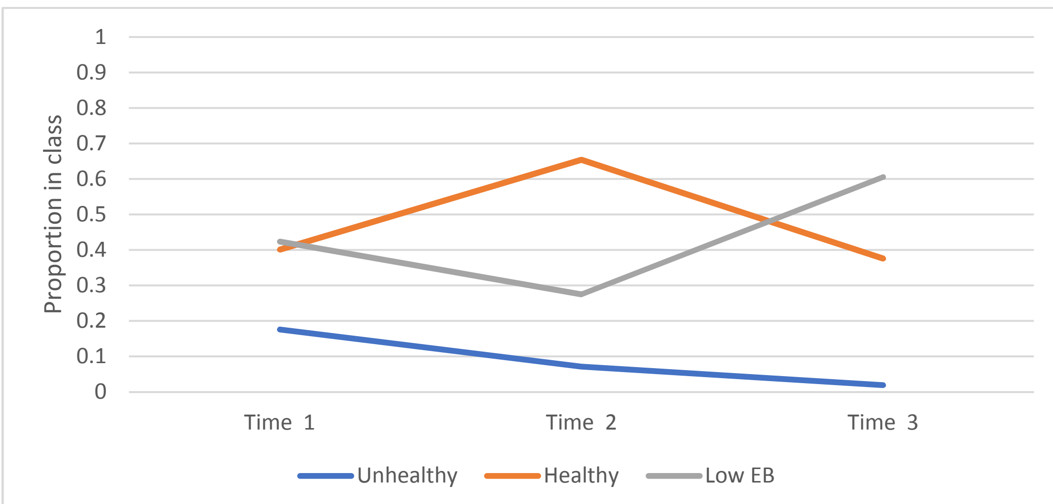
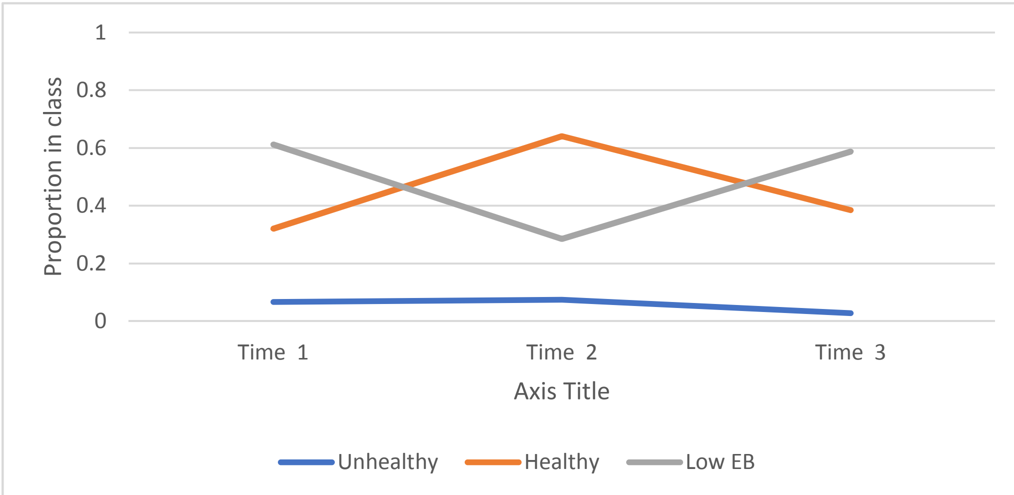


Figure 13. Classs Membership Trend for Older Participants



Tables

Table 1. Demographic and Variable Information

Variable		
N	4004	
Male (n, %)	1876	46.85
Female (n, %)	2128	53.15
Age (mean, SD)	54.85	9.93
Race (white)	99.12	
Non hisp	99.51	
Attended time 1	3702	
Attended time 2	3490	
Attended time 3	3000	
Attended all 3	2714	
Deceased	1404	
CVD diagnosis	315	
Waist to height ratio mean T1	0.5535304	0.08141
Waist to height ratio mean T2	0.5970286	0.0852200
Waist to height ratio mean T3	0.6089676	0.088289
Cigarette Use T1	668	18%
Cigarette Use T2	379	11.76%
Cigarette Use t3	243	8.15%
ETOH T1	598	16.15%
ETOH T2	622	17.91

ETOH T3	452	15.14%
Physical Activity T1	2067	57.61%
Physical Activity T2	2845	88.24%
Physical Activity T3	1775	60.73%
Fruit and Vegetable Intake T1	1666	49.87%
Fruit and Vegetable Intake T2	1474	49.31%
Fruit and Vegetable Intake T3	1413	52.55%

Table 2. Relative Fit Indices Comparison

Number of Latent Classes	LL	g2	df	AIC	BIC
2	-20851.6	2066.64	4082	2092.64	2174.47
3	**-20704.96**	**1773.35**	**4069**	**1825.35**	**1989.02**
4	-20686.31	1736.06	4052	1822.06	2092.74
5	-20656.78	1677.01	4031	1805.01	2207.89

Table 3. LTA Cluster Proportions by Timepoint

Status	Unhealthy	Healthy	Low EB
Time 1	0.1269	0.3657	0.5074
Time 2	0.0661	0.6552	0.2787
Time 3	0.0253	0.3817	0.593

Table 4. Item-Response Probabilities for All Timepoints

Item-Response Probabilities (rho)			
Class	Unhealthy	Healthy	Low Energy Balance

Physical Activity (“Yes”)	0.4949	0.9998	0.0009
Fruits and Vegetables (“Yes”)	0.2482	0.5561	0.4631
Cigarette Use (“No”)	0	0.9524	0.9313
Alcohol Use (“No”)	0.7161	0.8277	0.8635

Table 5. Transition Probabilities during First Transition

Time 1 (row) to Time 2 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.0777**	0.6322	0.2901
Healthy	0.0622	**0.6585**	0.2792
Low EB	0.066	0.6585	**0.2755**

Table 6. Transition Probabilities for Second Transition

Time 2 (row)to Time 3 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.054**	0.368	0.578
Healthy	0.0259	**0.3742**	0.5999
Low EB	0.0171	0.4027	**0.5802**

Table 7. Latent Class Membership Prevalence for Men

Men			
Status	Unhealthy	Healthy	Low EB
Time 1	0.1268	**0.4905**	**0.3827**
Time 2	0.0622	0.6594	0.2785
Time 3	0.0348	0.3819	0.5834

Table 8. Latent Class Membership Prevalence for Women

Women			
Status	Unhealthy	Healthy	Low EB
Time 1	0.1156	**0.259**	**0.6254**
Time 2	0.064	0.655	0.281
Time 3	0.0114	0.383	0.6056

Table 9. Latent Class Transition Probabilities for Men

First Transition - Men			
Time 1 (row) to Time 2 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.1234**	0.602	0.2746
Healthy	0.055	**0.6645**	0.2805
Low EB	0.0511	0.6718	**0.2771**
Second Transition			
Time 2 (row)to Time 3 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.0689**	0.3952	0.5359
Healthy	0.0349	**0.3857**	0.5793
Low EB	0.0268	0.3697	**0.6035**

Table 10. Latent Class Transition Probabilities for Women

First Transition - Women			
Time 1 (row) to Time 2 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.0284**	0.6599	0.3117

Healthy	0.0664	**0.6549**	0.2787
Low EB	0.0696	0.6541	**0.2762**
Second Transition			
Time 2 (row)to Time 3 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.0398**	0.3344	0.6258
Healthy	0.0122	**0.3667**	0.6211
Low EB	0.0029	0.4321	**0.565**

Table 51. Latent Class Membership Prevalence for Low Risk Waist-to-Height Ratio

Low Risk			
Status	Unhealthy	Healthy	Low EB
Time 1	0.1277	0.3643	0.508
Time 2	0.0873	0.6958	0.2169
Time 3	0.0203	0.3895	0.5902

Table 62. Latent Class Membership Prevalence for Moderate Risk Waist-to-Height Ratio

Moderate Risk			
Status	Unhealthy	Healthy	Low EB
Time 1	0.1296	0.3656	0.5048
Time 2	0.0612	0.6597	0.2791
Time 3	0.0178	0.3858	0.5965

Table 73. Latent Class Membership Prevalence for High Risk Waist-to-Height Ratio

High Risk			
Status	Unhealthy	Healthy	Low EB
Time 1	0.1012	0.3722	0.5266
Time 2	0.0418	0.5571	0.4011
Time 3	0.0254	0.3933	0.5812

Table 14. Latent Class Transition Probabilities for Low-Risk Waist-to-Height Ratio

Low Risk - 1st transition			
Time 1 (row) to Time 2 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.092**	0.6595	0.2485
Healthy	0.0697	**0.7145**	0.2158
Low EB	0.0987	0.6915	**0.2098**
2nd Transition			
Time 2 (row)to Time 3 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.0044**	0.4429	0.5527
Healthy	0.0286	**0.3756**	0.5958
Low EB	0	0.4127	**0.5873**

Table 15. Latent Class Transition Probabilities for Moderate-Risk Waist-to-Height Ratio

Moderate Risk 1st Transition			
Time 1 (row) to Time 2 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.0838**	0.6353	0.2809

Healthy	0.0578	**0.6631**	0.279
Low EB	0.0578	0.6635	**0.2788**
2nd Transition			
Time 2 (row)to Time 3 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.0494**	0.3279	0.6227
Healthy	0.0184	**0.3804**	0.6013
Low EB	0.0093	0.4113	**0.5794**

Table 16. Latent Class Transition Probabilities for High-Risk Waist-to-Height Ratio

High Risk 1st Transition			
Time 1 (row) to Time 2 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.0193**	0.5249	0.4558
Healthy	0.0649	**0.5303**	0.4048
Low EB	0.0298	0.5821	**0.3881**
2nd Transition			
Time 2 (row)to Time 3 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.2917**	0.2808	0.4275
Healthy	0	**0.3812**	0.6188
Low EB	0.0329	0.4219	**0.5452**

Table 87. Latent Class Membership Prevalence for Younger Participants

Younger			
Status	Unhealthy	Healthy	Low EB

Time 1	0.1758	0.4005	0.4237
Time 2	0.0708	0.6544	0.2748
Time 3	0.0186	0.3759	0.6055

Table 98. Latent Class Membership Prevalence for Older

Older			
Status	Unhealthy	Healthy	Low EB
Time 1	0.067	0.3209	0.6121
Time 2	0.0743	0.6406	0.2851
Time 3	0.0279	0.3846	0.5874

Table 19. Latent Class Transition Probabilities for Younger Participants

First Transition			
Time 1 (row) to Time 2 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.0557**	0.6459	0.2984
Healthy	0.0768	**0.6565**	0.2667
Low EB	0.0715	0.6559	**0.2726**
Second Transition			
Time 2 (row)to Time 3 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.0841**	0.3092	0.6067
Healthy	0.0133	**0.3786**	0.6081
Low EB	0.0143	0.3866	**0.5991**

Table 20. Latent Class Transition Probabilities for Older Participants

Older 1st Transition			
Time 1 (row) to Time 2 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.1722**	0.5571	0.2707
Healthy	0.0578	**0.6468**	0.2955
Low EB	0.0723	0.6465	**0.2812**
2nd Transition			
Time 2 (row)to Time 3 (column)	Unhealthy	Healthy	Low EB
Unhealthy	**0.0299**	0.4147	0.5554
Healthy	0.0314	**0.3674**	0.6011
Low EB	0.0196	0.4154	**0.565**

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