DISSERTATION

USING DATA SCIENCE TO UNDERSTAND PSYCHOSOCIAL DETERMINANTS OF HEALTH BEHAVIORS

Submitted by

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ABSTRACT

USING DATA SCIENCE TO UNDERSTAND PSYCHOSOCIAL DETERMINANTS OF HEALTH BEHAVIORS

Data science allows researchers to transform raw data into knowledge by combining technology and computer science skills with statistical and mathematical skills. Data scientists in academic research need substantive expertise in a particular field to help guide research questions, select proper measurement and analytical approaches, and help them understand the potential mechanisms and meaning underlying research findings. Further, having substantive expertise in health will enhance the collective knowledge regarding the relationships between exposures and chronic disease outcomes.

This dissertation provides concrete examples of data science's three areas of knowledge: 1) Substantive Expertise; 2) Technology & Computer Science; and 3) Statistics & Math to inform the collection, management, analysis, and interpretation of data related to unmodifiable and modifiable determinants of health (e.g. psychosocial determinants), health behaviors, and chronic disease.

This dissertation focuses on the substantive areas of chronic disease, health behaviors, and psychosocial and unmodifiable determinants of health behaviors, and demonstrates how these areas relate to one another to ultimately improve human health. Chronic diseases, such as cardiovascular disease, type 2 diabetes, and metabolic syndrome, negatively affect society by decreasing quality of life, causing negative short- and long-term health outcomes, and creating significant financial and social burdens. Reducing the burdens associated with these diseases requires a clear understanding of which variables predict the development, progression, and comorbidities associated with these largely preventable diseases.

Most of these diseases can be prevented by addressing behavioral risk factors, including weight status, physical activity/inactivity, sedentary behavior, and sleep. An individual's weight status and their physical activity participation predict cardiovascular disease-related outcomes and risk factors. Type 2

diabetes and metabolic syndrome are related to longer-term exposure to physical inactivity and sedentary behavior. Sleep disturbances and acute sleep deprivation increase the risk for cardiovascular disease and negative metabolic outcomes. Each of these health behaviors also interact with one another, resulting in potentially synergistic effects on chronic disease risk. Understanding health behaviors can help unravel the complex relationships among these health behaviors and chronic disease risk, and can potentially determine the dose of health behaviors required to confer positive health outcomes.

Improving health outcomes via changes in health behaviors also requires an understanding of how psychosocial determinants, such as stress, motivation, and action planning, relate to health behaviors. Psychosocial stress directly affects disease risk via physiological mechanisms, and indirectly affects disease risk through effects on physical activity and sleep behaviors. Greater psychosocial stress corresponds with worse chronic disease outcomes, less physical activity, and poorer sleep quality, and there is a reciprocal relationship between stress, physical activity, and sleep. More autonomous forms of motivation correspond with greater physical activity and more controlled forms of motivation correspond with lesser physical activity. Action planning significantly predicts physical activity and may close the gap between individuals' motivations, intentions, and behaviors. Each of these psychosocial determinants uniquely affect health behaviors and health outcomes.

Unmodifiable determinants, including age, sex, and race/ethnicity may correlate with or predict psychosocial determinants of health, health behaviors, and health outcomes. Proper statistical knowledge allows researchers to examine the direct and/or moderating effects of age, sex, and race/ethnicity in affecting the relationships between health behaviors and health outcomes, and properly examining these effects will allow researchers a more in-depth understanding of these relationships. As such, the health sciences can greatly benefit from data scientists who can combine their technological and statistical skills with substantive expertise to inform a clearer understanding of the relationships between unmodifiable and psychosocial determinants of health, health behaviors, and health outcomes.

Chapter 3 provides examples of how having expertise in health, along with technological skills, will enhance research. Study 1 demonstrates how technological skills enabled the development of a

Research Electronic Data Capture (REDCap) project that successfully increased the efficiency of data collection, improved data management and quality control/assurance, and accommodated the reporting needs and research goals of Colorado State University's Firefighter Testing Program (FTP), which is an ongoing, longitudinal program that captures data in Colorado firefighters related to psychosocial determinants of health, fitness, and cardiovascular disease risk. We found that migrating the FTP from paper-based data capture to REDCap required 15 months of project development, with subsequent field-testing and ongoing data collection resulting in continued changes to the FTP REDCap project. While this study primarily demonstrates technological skills, it is also shows how substantive expertise and statistical knowledge informed the FTP REDCap project.

Study 2 demonstrates how technology can be used to study health behaviors, and the purpose was to compare activPAL algorithm-estimated values for time in bed (TIB), wake time (WT) and bed time (BT) against self-report and the van der Berg algorithm. Baseline data from the Community Activity for Prevention Study were used. We used mixed-effects models, Bland-Altman plots, and equivalence tests to compare between TIB, WT, and BT values for all three methods. The activPAL algorithm was not equivalent to self-report (t(1084)=3.41, 90% CI [0.64, 0.91], p=1.00) or the van der Berg algorithm (t(982)=4.91, 90% CI [0.74, 0.97], p=1.00) in estimating TIB, but was equivalent to self-report for estimating BT (t(1143)=2.06, 90% CI [-0.47, -0.21], p=.02), and was equivalent to the van der Berg algorithm for estimating WT (t(986)=-2.69, 90% CI [0.21, 0.43], p<.01). The van der Berg algorithm was equivalent to self-report for TIB days (t(990)=6.11, 90% CI[-0.20, 0.015], p<.01), WT (t(1001)=-8.57, 90% CI [0.07, 0.21], p<.01), and BT (t(1124)=-4.17, 90% CI [0.16, 0.35], p<.01). Errors in the activPAL algorithm occurred when individuals participated in substantial lying down behaviors prior to BT or after WT. Overall, activPAL users can start taking advantage of the new algorithm, which enhances the utility of using the activPAL for examining 24-hour movement patterns in free-living individuals. Study 2 demonstrates how knowledge of technology can be leveraged to measure health behaviors and substantive expertise can be used to inform the interpretation of health behavior data.

Chapter 4 provides examples of combining statistical skills with substantive expertise to examine the relationships among unmodifiable and psychosocial determinants of health behaviors. Study 3 examined the longitudinal relationships between sex, race/ethnicity, autonomous motivation, controlled motivation, and PA planning with PA participation. We used data from Waves 2 (W2) through 7 (W7) of the NEXT Generation Health Study (NEXT), a nationally representative cohort study of U.S. 10th graders (N=2785). A two piece growth model indicated that PA declined from W2–W4 (b=-0.285, p<.001) and W4–W7 (b=-0.125, p=.042). Being female (b=-0.786, p<.001), or African American (b=-0.542, p=.001) or Hispanic (b=-0.501, p=.034) was associated with less PA at W2 compared to being male or White, respectively. Increased autonomous motivation was associated with higher PA (b: 0.196-0.384, p<.001). PA planning varied significantly between individuals and significantly predicted PA (b=0.445, p<.001). Controlled motivation was not significantly associated with PA. Our findings indicated that the adolescent-to-adult transition is characterized by transient changes in PA, suggesting this may be an appropriate timeframe for addressing PA.

Specifically, study 4 combines technological and statistical skills with substantive expertise to examine psychosocial determinants of health behaviors. The purpose of the study was to characterize firefighters' acute stress and tiredness and between- and within-person variability in stress and tiredness by duty status using a smartphone-based approach to ecological momentary assessment (EMA) in a convenience sample of 39 firefighters. EMA data were analyzed using mixed-effects location scale models. Firefighters' lowest stress levels were when off-duty (β=16.27) and their highest stress levels were when on-duty (β=24.47). Within-subject effects of duty status accounted for a larger proportion of variability for all duty types except when "on night/off day". Firefighters' lowest tiredness levels were when off-duty (β=24.71) and their highest levels were when on-duty (β=32.18). Within-subject effects of duty status accounted for a larger proportion of variability in tiredness for all duty types. We concluded that firefighters' more similar experiences to one another when they are on-duty might account for greater similarity in their stress and tiredness outcomes when on- versus off-duty.

These studies demonstrate how technological and statistical skills, paired with substantive expertise in health sciences can inform the collection, management, analysis, and interpretation of data related to unmodifiable and psychosocial determinants of health, health behaviors, and health outcomes. They also demonstrate how these skills can be applied to research in a variety of populations, as well as to research using various methodological and statistical approaches. Finally, these studies demonstrate that all three skills are needed to conduct effective and meaningful research studies, and how substantive expertise in a particular field, like the health sciences, provides a necessary foundation to employ technological and statistical skills in a meaningful way. Overall, this dissertation supports the assertion that we should intentionally foster the development of data scientists within the health sciences and capitalize on data scientists' skills to promote progress in research, clinical practice, and public health, with the long-term goal of improving human health.

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DEDICATION

Dedicated to my mom and my husband Lee.

Your teasing and love are what got me through this – Thank you and I love you.

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CHAPTER 1 – INTRODUCTION TO DATA SCIENCE

> "The ability to take data – to be able to understand it, to process it, to extract value from it, to visualize it, to communicate it – that's going to be a hugely important skill in the next decades." – Dr. Hal Varian, Chief Economist at Google and Professor at University of California Berkeley (Varian, 2009)

D.J. Patil and Jeff Hamerbacher coined the term "data scientist" in 2008, and the Harvard Business Review wrote an article in 2012 referring to data scientist as the sexiest job of the 21st century (Davenport & Patil, 2012). The increasing number of online courses with an emphasis on data science reflects the popularity of data science as a career; for example, a cursory search for "data science" courses in the online platform Coursera resulted in 875 matches (Coursera, 2019). The number of data science courses, specializations, and graduate degree certificates and programs offered by universities also continues to increase (Columbia University, 2018; Mobilize Center, 2019a; University of Florida, 2019; Worcester Polytechnic Institute, 2019). Despite the wide-spread adoption of the term "data scientist" and the growing popularity of data science as a career, little consensus exists regarding the definition of what makes an individual a data scientist (Davenport & Patil, 2012). The Harvard Business Review defines data scientists as "high-ranking professional(s) with the training and curiosity to make discoveries in the world of big data" (Davenport & Patil, 2012). The National Institutes of Health (NIH) defines data science as "the interdisciplinary field of inquiry in which quantitative and analytical approaches, processes, and systems are developed and used to extract knowledge and insights from increasingly large and/or complex sets of data" (National Institutes of Health, 2018). Wickham and Grolemund describe data science as "an exciting discipline that allows you to turn raw data into understanding, insight, and knowledge" (Wickham & Grolemund, 2017). Each of these definitions emphasizes data science as a field in which data, paired with curiosity or inquiry, allows individuals to uncover knowledge and insights about the world. The question is: How do data scientists transform data into knowledge?

Data scientists typically transform data into knowledge using analytical techniques like data mining or machine learning. They often work in the private sector for large tech companies like Google,

LinkedIn, and Uber, using their technological and statistical skills to transform data into knowledge about consumer behaviors, knowledge used to inform business processes, investments, and production decisions. However, widespread recognition exists regarding the ability for data science to transform a multitude of industries beyond the tech-space, including retail, telecommunications, agriculture, health, and the penal system (Bowne-Anderson, 2018). The NIH recognizes the value of data science and emphasizes the need to train data scientists capable of using Big Data to inform the advancement of scientific research, particularly in the field of biomedical sciences (National Institutes of Health, 2019). The NIH's recognition of the value data science can provide for advancing scientific research led to the growing presence of data scientists in academic research. The NIH's decision to fund a series of Big Data to Knowledge (BD2K) Centers of Excellence across the U.S. accounts for a large proportion of the growth of data scientists in academic research.

The NIH funded the BD2K Centers for the purpose of developing new analytical approaches, methods, software tools, etc. for advancing the Science of Big Data (National Institutes of Health, 2019). These centers use data science for a wide range of academic disciplines (National Institutes of Health, 2019). For example, Stanford's Mobilize Center uses data science for biomechanical modeling, behavioral and social modeling, statistical learning, and integrative modeling and prediction (Mobilize Center, 2019a). The results of these data science efforts inform mobility-related health applications, including cerebral palsy clinical planning, gait rehabilitation research, and weight management through physical activity (Mobilize Center, 2019b). The University of Florida's Data Science Research Lab uses data science to generate predictive models and identify important physiological markers of health to facilitate patient care in perioperative environments (University of Florida College of Medicine, 2019). Other BD2K Centers use data science to identify causal relationships between biomedical variables and health outcomes, to harness the power of mobile sensors (i.e. smart watches, accelerometers, GPS, etc.) to provide insights into health conditions like drug addiction, smoking, and obesity, and to develop and validate biomarkers for use in research (MD2K, 2019). Each of these centers uses database management systems, machine or deep learning algorithms, probabilistic modeling, and data mining, along with other

approaches, to process, extract meaning from data, and identify significant relationships between variables to inform research.

Extracting meaningful knowledge from data is a primary goal of data scientists. However, achieving this goal requires substantial investment in managing and cleaning data. Data scientists use approximately 80% of their time finding, cleaning, and/or organizing data (Bowne-Anderson, 2018; Crowdflower, 2016). Properly managing and cleaning data is important because data scientists (and all researchers) cannot trust analytical outcomes until data have been properly cleaned and quality assured. Unfortunately, data management is not particularly enjoyable, with 57% of data scientists indicating that the least enjoyable part of their job is cleaning and organizing data (Crowdflower, 2016). The good news is that there is a light at the end of the tunnel, because data scientists are using their technical skills, such as their knowledge of machine learning, to build automated approaches for cleaning and organizing data (Bowne-Anderson, 2018). This automation will remove much of the drudgery from data scientists' day-to-day tasks, but it also leads to the question: 1) Are data scientists automating their jobs into obsolescence?

No, they are not; rather, this automation allows data scientists to capitalize on their other skills, such as the ability to interpret and communicate the meaning underlying data findings. Many data scientists argue that increased automation of data management tasks shifts an emphasis away from data scientists needing to know specific techniques, like how to clean and organize data or how to build and use deep learning infrastructures, towards their skills related to rapid, independent learning and communicating data findings (Bowne-Anderson, 2018; Davenport & Patil, 2012). Davenport and Patil support the value of these skills over technical skills, stating:

> "More enduring will be the need for data scientists to communicate in a language that all their stakeholders understand and to demonstrate the special skills involved in storytelling with data, whether verbally, visually, or – ideally – both." (Davenport & Patil, 2012)

The ability to communicate what data means requires knowledge beyond technology/computer science and statistics/math. Understanding the meaning underlying data and communicating said meaning requires data scientists to possess substantial expertise in a specific field. Wickham and Grolemund

acknowledge this need for substantive expertise through their conceptualization of data scientists as combining three areas of knowledge: 1) Substantive Expertise in a particular field; 2) Technology & Computer Science; and 3) Statistics & Math (Wickham & Grolemund, 2017).

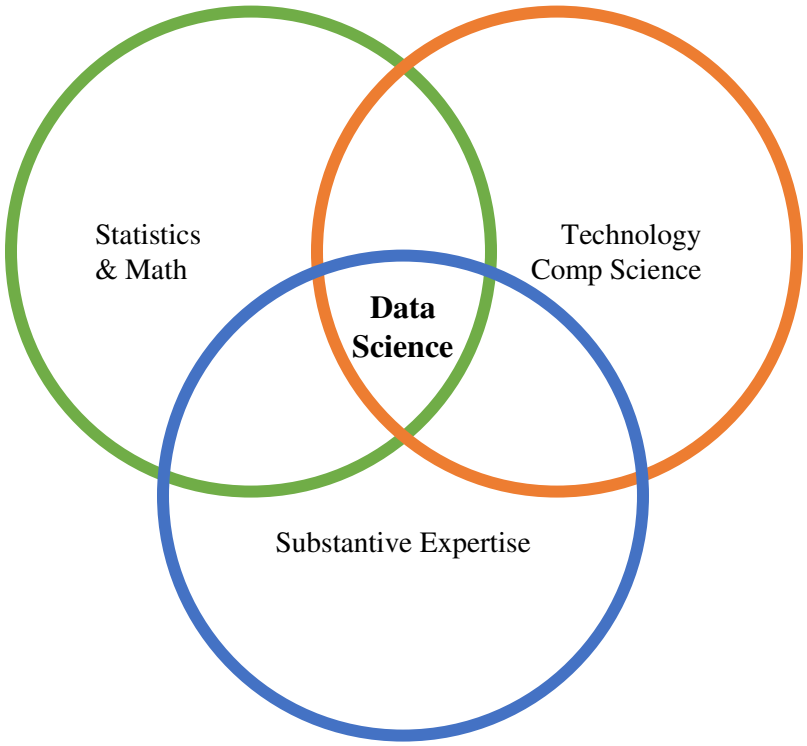


Figure 1. Data scientists' three areas of knowledge

Possessing substantive expertise in a field is particularly important for data scientists working in academic research. Industry-based data scientists may be successful by only employing their technological and statistical skills, typically acting as number crunchers for senior executives and other decision-makers. Academic data scientists cannot rely solely on said skills; rather, they require substantive expertise to support their research. Substantive expertise in a given field guides the questions academic data scientists ask, how they measure outcomes, and the analytical approaches they use to understand research outcomes. Substantive expertise also allows academic data scientists to identify potential mechanisms (i.e. physiological or psychological) underlying the relationships they discover. Perhaps more importantly, substantive expertise allows academic data scientists to identify when the

relationships they identify do not make sense from a theoretical, conceptual, and/or physiological perspective. This knowledge of the theoretical underpinnings or physiological mechanisms driving a discovered relationship is necessary for informing future research and interventions. Additionally, this substantive knowledge provides academic data scientists with the necessary expertise to communicate the meaning underlying data outcomes. Overall, academic data scientists require substantive expertise in a field, not just technological or statistical expertise. Indeed, many examples exist regarding significant findings discovered by mining Big Data, findings that, while statistically meaningful, are practically meaningless or theoretically unsound.

For example, through data mining, data scientists found that Miss America's age correlates almost perfectly with the number of murders committed by steam, hot vapors, and hot objects across time, and that the S&P 500 Index correlates with butter production in Bangladesh, accounting for 99% of the variation in Bangladesh's butter production (Piatetsky & Rajpurohit, 2014). While these findings may appear interesting or intriguing, they also seem odd, inexplicable, or even false. They are, in fact, false, and occurred because of data scientists committing one of the cardinal sins of data mining, namely, 'overfitting the data' (Piatetsky & Rajpurohit, 2014). Overfitting data occurs when researchers test too many hypotheses or, in the case of data mining, allow for the presence of too many potential correlations, eventually leading to interesting but spurious findings. This results in inaccurate or misleading findings and bolsters already-existing public distrust of scientists and their research (Resnick, 2017). These examples demonstrate how technological and statistical knowledge may be insufficient foundations upon which to build meaningful knowledge – the true goal of data science. They also demonstrate the need for substantive expertise to explain data-driven phenomena. Successfully communicating with others about data findings requires substantive expertise in the field and the ability to identify when findings are meaningful, but what is meaningful?

The question of 'what is meaningful' underlies the NIH's interest in promoting the development and training of data scientists. Specifically, the NIH's promotion of data science and the development of an academic data science work force comes in part from the recent 'replication crisis', in which the

findings from previous landmark studies have proven unrepeatable, a crisis resulting in public distrust of science, scientists, and the research process (National Institutes of Health, 2018; Resnick, 2017). For example, a paper in Science attempting to replicate 100 findings published in psychology journals found that only 39% could be replicated (Loken & Gelman, 2017). In economics research, only 60% could be replicated (Resnick, 2017). The typical scientific definition of 'what is meaningful' likely underlies this replication crisis. John Ioannidis stated that:

> "the high rate of non-replication (lack of confirmation) of research discoveries is a consequence of the convenient, yet ill-founded strategy of claiming conclusive research findings solely on the basis of a single study assessed by formal statistical significance, typically for a *p*-value less than 0.05" (Ioannidis, 2005).

Emphasis on the *p*-value as the metric for qualifying research findings as "meaningful" continues to be scrutinized, because a given *p*-value does not indicate whether or not a finding is truly meaningful. Rather, finding a statistically significant *p*-value, such as $p<.05$, only indicates that the findings in a study are likely to generalize to the broader population and, simultaneously, indicates that the findings likely did not arise due to chance, in which case they would not be generalizable to the population in question (Geher, 2016). Indeed, Ioannidis argues that the replication crisis could be due to the penchant of researchers to focus on the claims of one research study, simply because said study found a statistically significant *p*-value for a given relationship, without considering other studies examining the same outcome (Ioannidis, 2005). Focusing on the outcomes of one study is inherently problematic because probability dictates that one set of researchers may falsely find a significant relationship when a true relationship doesn't exist, and if the scientific community happens to focus on that one false study, it leads to false assumptions regarding the relationship between variables (Ioannidis, 2005). Such assumptions can lead researchers down a false trail and/or prevent them from pursuing more fruitful research questions. Well-trained data scientists recognize these limitations of using $p<.05$ to indicate statistical significance, and recognize that statistical significance does not reflect the actual meaningfulness of outcomes. However, if data scientists and researchers cannot rely on $p<.05$ to indicate whether results are meaningful, what metric can they use to establish meaningfulness?

Some researchers suggest lowering the value for statistical significance from $p<.05$ to $p<.005$, a move that would increase the likelihood of reproducible results (Resnick, 2017). Such a change makes sense from a mathematical perspective because it requires six times stronger evidence, thereby increasing the burden of proof scientists should achieve prior to further pursuing a specific research question (Resnick, 2017). Meeting this criteria of $p<.005$ would also require a 70% increase in sample size (Resnick, 2017). Critics arguing against this change say it will stifle scientific progress, particularly for new researchers with low budgets, and that good researchers know how to follow-up with appropriate studies (Resnick, 2017). Critics also argue that this change keeps the scientific community fixated on *p*-values, a fixation that fails to indicate whether or not research findings are truly meaningful (Resnick, 2017). I agree that this fixation on *p*-values is problematic because it does not answer the question of meaningfulness, though decreasing statistical significance to $p<.005$ does increase the likelihood that research findings *could* be meaningful. For example, the Science paper about the replication crisis found that studies yielding results with *p*-values <.01 were more likely to be replicated (Loken & Gelman, 2017; Resnick, 2017). It may be more appropriate to shift away from focusing on *p*-values towards other measures of meaningfulness, like effect size or clinical significance. Indeed, many researchers argue in favor of examining effect sizes or clinical significance to identify meaningful research findings (Johnson, 1999; Leung, 2001; Nakagawa & Cuthill, 2007; Page, 2014; Resnick, 2017; Sullivan & Feinn, 2012).

Identifying findings as being clinically meaningful typically means that the smallest expected change in the outcome is sufficient or important enough that it would change patient management (Kazis, Anderson, & Meenan, 1989; Leung, 2001; Page, 2014). Clinical meaningfulness also requires balancing beneficial and harmful changes – like balancing statin-related improvements in low density lipoprotein (LDL) cholesterol levels with statin-related side effects, such as difficulty sleeping or muscle aches (Kazis et al., 1989; Leung, 2001; Page, 2014). Clinical meaningfulness strongly relates to effect size, with effect size indicating the magnitude of difference or change between two groups that is accounted for by a drug, intervention, or other variable (Kazis et al., 1989; Sullivan & Feinn, 2012). Researchers can use several indices to quantify effect size, including Cohen's *d*, odds ratios, relative risk, and the r^2 coefficient

of determination (Kazis et al., 1989; Sullivan & Feinn, 2012). Using effect size helps researchers and clinicians quantify the meaningfulness of outcomes; whereas, the *p*-value only provides information regarding whether an effect likely exists (Kazis et al., 1989; Sullivan & Feinn, 2012). For example, a study might find a statistically meaningful decrease in blood pressure levels among individuals who meet physical activity recommendations; however, the effect of meeting physical activity recommendations could be small, perhaps only decreasing blood pressure by 1 mm mercury (Hg). Such an effect would likely be considered practically or clinically meaningless, despite being statistically significant. In contrast, if a study found a 10 mm Hg decrease in blood pressure related to meeting physical activity recommendations that would represent a much larger effect size and clinically meaningful change in blood pressure. Gene V. Glass understood the value of effect size when interpreting research outcomes, stating that:

> "Statistical significance is the least interesting thing about the results. You should describe the results in terms of measures of magnitude – not just, does a treatment affect people, but *how much does it affect them.*" (Sullivan & Feinn, 2012) (Emphasis added)

However, not all scientists agree with focusing entirely on effect sizes (Ioannidis, 2005). Ioannidis states that the presence of too large of effect sizes likely indicates large bias in a study, and suggests that researchers should consider whether errors in their data collection or analyses resulted in such large effect sizes (Ioannidis, 2005). Ioannidis' argument supports the need for data scientists to be capable of providing plausible explanations for their findings and not to take findings at face-value. This need exists regardless of whether scientists use *p*-values, effect sizes, or another metric to identify whether research findings are meaningful. Data scientists with substantive expertise in a specific field of study possess the necessary skills to identify plausible explanations underlying research outcomes and to understand the differences between *p*-values and effect sizes. These skills provide substantial value because they help inform the progression of research based on a nuanced understanding of a specific scientific field and statistical analyses and outcomes. These skills also make data scientists uniquely positioned to identify meaningful research findings and to communicate them to researchers, clinicians, and the general public.

Over the past decade, dramatic changes in technology and statistics, combined with the Big Data revolution, fostered the growth of data science and the need for well-trained data scientists. The Big Data revolution provides researchers with access to massive quantities of data across of a variety of fields, including genetics, clinical studies, electronic medical records, and observational data collected from wearable devices, like smartwatches, fitness trackers (i.e. Fitbit or Apple Watch), and so forth. The large quantity of data encompassing a variety of fields provides researchers with the unique opportunity of identifying previously unknown relationships that may have the capacity to improve the human condition and inform the progress of scientific research. However, analyzing Big Data does not automatically result in identifying meaningful scientific outcomes. As previously mentioned, mining Big Data can result in identifying spurious or meaningless relationships, and data scientists who are solely capable of employing technological and/or statistical skills without the necessary substantive expertise may undermine the inherent value of Big Data, thus wasting the opportunities it affords to improve the human condition. This reinforces Davenport and Patil's acknowledgment that data scientists' technological and statistical skills may prove to be less enduring than their ability to communicate research findings in a meaningful way (Davenport & Patil, 2012), an ability that is largely dependent upon data scientists' substantive expertise in a given field. Data scientists with substantive expertise provide the best opportunity for harnessing the power of Big Data and advances in technology and statistics for improving the human condition.

The health sciences represent a field that should capitalize on data scientists' technological and statistical abilities for the purpose of improving human health, such as by reducing chronic disease risk. Data scientists with substantive expertise in health behaviors and chronic disease can use data captured via electronic medical records, wearable devices, and smartphone-based assessments, among others, to enhance collective knowledge regarding the relationships between psychosocial determinants of health, health behaviors, and chronic disease. Such data scientists can combine their substantive expertise in health behaviors and outcomes with their technological and statistical skills to identify meaningful outcomes that can inform how researchers, clinicians, and the general public think about health. These data scientists can inform future research studies, interventions, clinical practice, and public health

recommendations to improve human health and reduce chronic disease risk. As such, we should intentionally foster the development of data scientists within the health sciences and capitalize on data scientists' skills to promote progress in research, clinical practice, and public health, and to enhance human health outcomes.

This dissertation provides examples of combining data scientists' three areas of knowledge: 1) Substantive Expertise; 2) Technology & Computer Science; and 3) Statistics & Math (Wickham & Grolemund, 2017), to inform the collection, management, analysis, and interpretation of data related to unmodifiable and psychosocial determinants of health, health behaviors, and health outcomes. Chapter 2 provides substantive information on chronic disease, health behaviors, and psychosocial and unmodifiable determinants of health. Chapter 3 includes two studies using technological and computer science skills. Study 1 provides an example of how to use technology and computer science to enhance the management and quality control and assurance of health-related data, and Study 2 provides an example of how to use technology, specifically an accelerometer/inclinometer, to examine individuals' health behaviors. Chapter 4 includes two studies using statistical and mathematical skills. Specifically, study 3 provides a practical example of combining statistical and mathematical knowledge with substantive expertise to examine the relationships among unmodifiable and psychosocial determinants of health and health behaviors, and Study 4 provides a practical example of combining technological and statistical skills with substantive expertise to examine psychosocial determinants of health behaviors. The studies in this dissertation employ a variety of populations, methodological and statistical approaches, and research outcomes of interest, thus demonstrating how data scientists' skills can inform a multitude of studies in the health sciences to increase knowledge, with the long-term goal of improving human health.

CHAPTER 2 – SUBSTANTIVE EXPERTISE IN CHRONIC DISEASE, HEALTH BEHAVIORS, AND PSYCHOSOCIAL AND UNMODIFIABLE DETERMINANTS OF HEALTH

Introduction

Chronic diseases represent a huge public health burden in the United States (U.S.) and globally. Many of these diseases, such as cardiovascular disease (CVD), type 2 diabetes mellitus (DM), and metabolic syndrome, negatively affect quality of life, short- and long-term health outcomes, and lifespan. The significant public health burden associated with CVD, DM, and other non-communicable diseases resulted in the World Health Organization (WHO) establishing the goal of reducing:

> "the preventable and avoidable burden of morbidity, mortality and disability due to non-communicable diseases by means of multi-sectoral collaboration and cooperation at national, regional and global levels, so that populations reach the highest attainable standards of health and productivity at every age and those diseases are no longer a barrier to well-being or socioeconomic development." (World Health Organization, 2013)

This goal supports the WHO's vision to create a world free from the burden of non-communicable diseases (World Health Organization, 2013). The WHO established nine global targets to help achieve this vision, with one target focused on achieving a 25% relative reduction in the risk of premature mortality due to CVD, cancer, diabetes, and chronic respiratory diseases (World Health Organization, 2013). Other targets focus on chronic disease risk factors, such as reducing the prevalence of high blood pressure, DM, and obesity (World Health Organization, 2013). Two targets focus on increasing access to basic medical care, affordable medications, counseling, etc. (World Health Organization, 2013). Finally, four focus on improving health behaviors related to the development of chronic disease, such as reducing tobacco use and increasing participation in physical activity (PA) (World Health Organization, 2013). The WHO's recognition of the strong relationship between health behaviors and the risk for CVD, DM, and other preventable chronic diseases underlines the importance of acknowledging the role of health behaviors in preventing chronic disease and improving overall health.

Research indicates that engaging in health promoting behaviors, like PA and healthy eating, and avoiding health compromising behaviors, like tobacco use and excessive alcohol use, helps reduce chronic disease risk. Health promoting behaviors directly and indirectly reduce chronic disease risk and improve risk factors for chronic disease. For example, participating in PA directly reduces the risk for DM by promoting cellular glucose uptake, thereby decreasing blood glucose levels and reducing the quantity of insulin the pancreas must produce to lower blood glucose levels. PA indirectly reduces the risk for CVD, DM, and metabolic syndrome by reducing the risk for overweight/obesity. Researchers, interventionists, physicians, and public health professionals need to understand the direct and indirect effects of health behaviors to effectively reduce chronic disease risk by targeting these behaviors via research studies, interventions, medical care, and public health policies.

Understanding the relationship between health behaviors and chronic disease is an import first step in combatting chronic disease. However, focusing solely on health behaviors often fails to reduce chronic disease risk, requiring additional understanding of the psychosocial determinants of said health behaviors. For example, research suggests that psychosocial determinants like stress, motivation, and action planning, affect engagement in PA, healthy eating, and other health behaviors. Therefore, researchers and public health professionals need to understand the causal relationships among these psychosocial determinants, health behaviors, and chronic disease. Finally, understanding these relationships also requires knowledge of the role of unmodifiable variables, such as sex, race/ethnicity, and age.

Characterizing how unmodifiable variables, psychosocial determinants, health behaviors, and chronic diseases relate to one another requires consideration of the directionality and temporality of these relationships, which is achievable by using appropriate statistical models. For example, cross-sectional analyses allow researchers to examine how unmodifiable variables, like sex, may moderate the relationship between PA participation and chronic disease. Longitudinal analyses allow researchers to understand how psychosocial determinants, like motivation, affect PA participation across time, thereby

affecting subsequent chronic disease. Such analyses have the power to inform future research studies, interventions, and public health recommendations to reduce chronic disease risk.

Therefore, the purposes of this chapter are to:

1. Describe chronic diseases and their effects on human health and society;
2. Synthesize current knowledge regarding how health behaviors affect chronic disease;
3. Examine the relationships between psychosocial determinants of health behaviors, health behaviors, and chronic disease; and
4. Identify how unmodifiable variables correlate with or predict psychosocial determinants of health, health behaviors, and chronic disease.

Integrating this information provides the necessary foundation for informing the questions researchers ask, as well as for informing the use of technological and statistical approaches for answering questions concerning the relationship between psychosocial determinants, health behaviors, and chronic disease.

Chronic Disease

Cardiovascular Disease

CVDs represent the leading cause of death in the U.S. and worldwide (Centers for Disease Control and Prevention, 2017a; World Health Organization, 2017). One-in-four deaths in the U.S. are due to CVD (Centers for Disease Control and Prevention, 2017a) and, in 2011, CVD was listed as the underlying cause of 31.3% of deaths in the U.S. (Mozaffarian et al., 2015; National Center for Health Statistics, 2011). Coronary heart disease (CHD) represents the most common type of CVD in U.S., killing over 370,000 people annually (Centers for Disease Control and Prevention, 2018), and eliminating all forms of CVD could increase life expectancy in the U.S. by almost 7 years (Danaei et al., 2009). CVD also accounts for the largest proportion of worldwide deaths due to non-communicable diseases (McAloon, Osman, Glennon, Lim, & Hayat, 2016). In 2016, approximately 17.9 million people died from CVDs, accounting for 31% of all global deaths, and CVDs account for one-third of premature deaths worldwide (World Health Organization, 2017). As such, the World Health Assembly Ministers of Health set the goal of reducing premature deaths due to non-communicable diseases by 25% by 2025 (S. C.

Smith et al., 2012). Achieving this goal would delay or prevent the number of premature deaths attributable to CVDs by millions of people annually (Kontis et al., 2014; S. C. Smith et al., 2012).

While CVD-related mortality rates are a serious cause for concern, advances in biomedical research, emergency response systems, and the treatment and prevention of CVD have lowered mortality rates (American Heart Association, 2017). Specifically, from 2000 to 2011, CVD-related mortality rates declined by 3.7% yearly, and stroke mortality rates declined by 4.5% yearly (American Heart Association, 2017). Age-standardized mortality rates for other cardiovascular and circulatory diseases also decreased by 10% to 50% from 1990 to 2016 (Mokdad et al., 2016). Unfortunately, these declines have attenuated, decreasing by less than 1% per year since 2011 (American Heart Association, 2017). Alarmingly, vulnerable populations show increased CVD mortality rates and, in 2015, overall CVD mortality rates increased by 1% – the first increase since 1969 (American Heart Association, 2017). Along with threatening mortality, CVD morbidities also threaten public health.

CVD accounts for a large proportion of morbidities, with 41.5% of Americans having at least one CVD condition, such as CHD, cerebrovascular disease, congestive heart failure (CHF), hypertension (HTN), rheumatic heart disease, or pulmonary embolism, among others (American Heart Association, 2017; World Health Organization, 2017). In the U.S., the prevalence of CVD morbidities varies by the type of CVD, with HTN representing the most prevalent morbidity, affecting 96.1 million people (American Heart Association, 2017). CHD affects 16.8 million people, followed by stroke, CHF, and atrial fibrillation (7.5, 5.8, and 5.2 million people, respectively) (American Heart Association, 2017). The American Heart Association (AHA) predicts an increased prevalence of CVD-related morbidities over the next two decades, projecting that, by 2035, 45% of the U.S. population will have some form of CVD, with an additional 43 million people experiencing HTN, CHD, stroke, CHF, and atrial fibrillation (American Heart Association, 2017).

This high prevalence of CVD morbidities represents a significant financial burden, and CVD is the most expensive chronic disease in the U.S., costing approximately $555 billion per year (American Heart Association, 2017). In contrast, diseases like DM and Alzheimer's cost $200 billion and $225

billion annually, respectively (American Heart Association, 2017). The AHA projects that increasing CVD-related expenses over the coming years will surpass the cost for other prevalent chronic diseases, like DM and Alzheimer's, with CVD-related costs increasing to $1.1 trillion by 2035. The Baby Boomers' eminent transition from middle-age into older adulthood (65 years and older) or old age (80+ years) account for this dramatic increase in CVD-related costs (American Heart Association, 2017). Direct CVD-related medical costs are predicted to increase by 135% from 2015-2035, and indirect costs associated with lost productivity at work and at home are projected to increase 55% from 2015-2035 (American Heart Association, 2017). Current and future CVD-related costs represent a substantial financial burden for Americans, particularly for underserved populations; however, financial costs only represent part of the concern related to the increased prevalence of CVD morbidities.

Along with the financial costs, the social costs of CVD cause substantial concern. Disability adjusted life years (DALYs) provide one metric for estimating the societal burden of CVD, because they combine years of life lost and years lived with disability (McAloon et al., 2016). Years of life lost accounts for the frequency and age at which death due to CVD occurs, and years lived with disability accounts for years lost from ideal health status (McAloon et al., 2016). One DALY equates to one year of healthy life lost (McAloon et al., 2016). CVD accounted for 398 million worldwide DALYs in 2012, and CVD accounts for two of the top ten global causes of DALYs, making it the largest fatal and non-fatal health burden in the world (McAloon et al., 2016).

The high prevalence of CVD-related mortality and morbidity represents a huge public health concern, affecting the physical health, financial health, and quality of life of individuals and the population as a whole. As such, reducing CVD-related morbidities and mortality has the potential to promote greater physical, financial, and social well-being for individuals and society at large. However, chronic diseases other than CVD also represent a significant health burden. For example, while CVD represents the most prevalent, expensive, and fatal health burden in the world, type 2 DM also increases morbidity and mortality. DM occurs when either the pancreas fails to produce sufficient insulin, or to

effectively use insulin, to lower blood glucose levels (World Health Organization, 2016). While there are many types of DM, type 2 DM comprises the largest health burden of all types of DM.

Type 2 Diabetes Mellitus

DM prevalence rates have continued increasing, with rates among U.S. adults being 6.2% from 1988-1994, followed by an increase to 9.9% from 2005-2010, and finally to 9.4% in 2015 (Centers for Disease Control and Prevention, 2019b; Mozaffarian et al., 2015; Selvin, Parrinello, Sacks, & Coresh, 2014). Approximately 8.1 million U.S. adults have undiagnosed DM, and 80.8 million U.S. adults have prediabetes (Mozaffarian et al., 2015; Selvin et al., 2014). The prevalence of type 2 DM also increased by 30.5% in youth between 2001 and 2009 (Dabelea et al., 2014; Mozaffarian et al., 2015). Overall, DM prevalence rates in the U.S. are expected to increase to at least 12.0% by 2050, with the largest expected increases among individuals 65-74 years of age (220% increase) and 75+ years of age (449% increase) (Mozaffarian et al., 2015; Narayan, Boyle, Geiss, Saaddine, & Thompson, 2006). Global prevalence rates parallel the U.S., with 8.5% of adults living with DM worldwide, a 100% increase from 1980 (World Health Organization, 2016). Additionally, 24% to 62% of people have undiagnosed or untreated DM (Cho et al., 2018; World Health Organization, 2016). Estimates predict global DM prevalence rates will increase to anywhere from 9.9% to 11.8% by 2030 (Bommer et al., 2018; Cho et al., 2018). These high DM-related prevalence rates cause concern, particularly considering the high DM-related morbidity rates.

DM represents the seventh leading cause of death in the U.S., with a crude death rate of 24.7/100,000 people (Centers for Disease Control and Prevention, 2019b), and accounts for 5.2% of deaths worldwide (Mozaffarian et al., 2015). DM-related mortality often results due to comorbidities, including CVDs, with at least 68% of U.S. adults with DM dying from some form of CVD, and CVD mortality rates are 2-4 times higher among adults with DM (Centers for Disease Control and Prevention, 2019b; McAloon et al., 2016; Mozaffarian et al., 2015). Chronic kidney disease also accounts for high DM-related mortality rates in the U.S., with rates increasing by 61.1% from 1990 to 2016 (Mokdad et al., 2016). Globally, DM accounts for approximately 9.9% of all-cause mortality (Cho et al., 2018), and CVD accounts for 60% of global deaths in people with DM (McAloon et al., 2016). Individuals with DM

experience shorter lifespans, with U.S. males and females with DM living an average of 7.5 and 8.2 fewer years than non-diabetics, respectively (Franco, Steyerberg, Hu, Mackenbach, & Nusselder, 2007; Mozaffarian et al., 2015). The high mortality rates and reduced lifespans associated with DM continue increasing, and projections suggest that global DM-related deaths will increase to approximately 4.57 million by 2030 (Bommer et al., 2018).

DM-related morbidities cause even greater concern than DM-related mortalities. DM increases the risk of developing CVD and the hazard ratios (HR) for developing CVD are 2.4 among males with DM and 2.5 among females with DM (McAloon et al., 2016; Mozaffarian et al., 2015). These associations exist because many CVD risk factors commonly co-occur with DM. For example, diabetics experience high obesity rates, with 26.1%, 43.5%, and 17.8% of adults with DM being overweight, obese, or severely obese (BMI ≥ 40), respectively (Centers for Disease Control and Prevention, 2019b; Mozaffarian et al., 2015). These high obesity rates among diabetics correspond with increased CVD risk, and obese diabetic males and females experience a 86.9% and 78.8% lifetime CVD risk, compared to 78.6% and 54.8% in normal weight diabetic males and females, respectively (Fox et al., 2008; Mozaffarian et al., 2015). Weight status represents a common risk factoring underlying DM and CVD.

DM also affects the risk for CVD-related events, including acute myocardial infarction (MI), atrial fibrillation, CHF, stroke, or death (Bahrami et al., 2008; Booth, Kapral, Fung, & Tu, 2006; Goldstein et al., 2011; Hunt et al., 2009; R. R. Huxley, Filion, Konety, & Alonso, 2011; Kissela et al., 2005; Mozaffarian et al., 2015). DM also clusters with CVD risk factors, and prevalence rates of HTN and elevated LDL are 75%-85% and 70%-80% among adults with DM, respectively (Mozaffarian et al., 2015; Preis et al., 2009; Selvin et al., 2014). Diabetics exhibit more severe subclinical atherosclerosis, as measured by coronary artery calcium, and the extent of coronary artery calcium is a stronger predictor of CHD and CVD in people with DM than among those without DM (Mozaffarian et al., 2015). Finally, coronary artery calcium progression occurs to a greater extent among diabetics and said progression thereby predicts future CVD event risk (Blaha et al., 2011; Malik et al., 2011; Mozaffarian et al., 2015; Wong et al., 2012).

Some of the most debilitating DM-related comorbidities include blindness, kidney disease, and limb amputation (World Health Organization, 2016). In 2010, diabetic retinopathy accounted for 1.9% of moderate or severe visual impairment and 2.6% of blindness globally (World Health Organization, 2016). Approximately 35% of diabetics experience retinopathy and 7% experience vision-threatening retinopathy (World Health Organization, 2016). Globally, DM, HTN, or a combination thereof account for 80% of end-stage renal disease, with 12-55% of cases solely attributable to DM (World Health Organization, 2016). Diabetics also experience amputation rates that are 10 to 20 times higher than non-diabetics (World Health Organization, 2016). Fortunately, recent improvements in DM treatment and maintenance of normal blood glucose levels has reduced amputation rates among diabetics by 40-60% (World Health Organization, 2016). However, despite these improvements, DM is an expensive disease.

DM accounts for 1 in every 5 healthcare dollars spent in the U.S., costing an estimated $245 billion in 2012 (American Diabetes Association, 2013; Mozaffarian et al., 2015). These costs include $176 billion from direct medical costs and $69 billion from indirect costs due to reduced productivity (American Diabetes Association, 2013; Mozaffarian et al., 2015). Individuals with DM cost approximately 2.3 times more than those with DM, with annual medical expenditures of diabetics averaging $13,700/year (Centers for Disease Control and Prevention, 2019b). Globally, DM accounts for 12% of total health expenditures (Zhang et al., 2010), including $860 billion from direct costs and $460 billion from indirect costs (Bommer et al., 2018). Globally, direct costs of DM are projected to increase by 2030, costing anywhere from $490.1 billion to $1.7 trillion (Bommer et al., 2018; Zhang et al., 2010). Indirect costs are predicted to increase to $780 billion (Bommer et al., 2018). Along with substantial financial costs, DM ranked as the fourth leading cause of DALYs in the U.S. in 2016, and DALYs due to DM-related chronic kidney disease increased by 127.6% from 1990 to 2016, rising from the 38th to the 21st leading cause of DALYs (Mokdad et al., 2016). DM represents a chronic disease that causes significant physical, financial, and social burdens in the U.S. and globally. However, one other chronic disease, metabolic syndrome, also requires consideration, particularly due its shared characteristics with CVD and DM.

Metabolic Syndrome

Metabolic syndrome refers to a cluster of metabolic abnormalities that lead to increased risk for CVD and type 2 DM (Mozaffarian et al., 2015). Historically, the precise clinical definition of metabolic syndrome varied between organizations; however, in 2009, multiple organizations issued a joint scientific statement to harmonize the definition of metabolic syndrome (Alberti et al., 2009). As such, individuals are diagnosed as having metabolic syndrome when they exhibit at least three of the following five risk factors: 1) Fasting plasma glucose ≥100mg/dL or undergoing drug treatment for elevated glucose; 2) high density lipoprotein (HDL) cholesterol <40mg/dL in males or <50mg/dL in females or undergoing drug treatment for reduced HDL cholesterol; 3) Triglycerides ≥150mg/dL or undergoing drug treatment for elevated triglycerides; 4) Waist circumference >102 cm in males or >88 cm in females for people of most ancestries living in the U.S.; and 5) Blood pressure ≥130 mmHg systolic or ≥85 mmHg diastolic, or undergoing drug treatment for HTN or antihypertensive drug treatment in a patient with a history of HTN (Alberti et al., 2009). Among adults, the age-adjusted prevalence of metabolic syndrome was 22.9% in 2009-2010 (Beltran-Sanchez, Harhay, Harhay, & McElligott, 2013; Mozaffarian et al., 2015). Globally, prevalence rates are also high, ranging from 15.1% in northwest China, to 29.6% in Brazil, with the highest prevalence rates occurring among indigenous populations (Australian Aborigines – 33.0% and Torres Strait Islanders – 50.3%) (de Carvalho Vidigal, Bressan, Babio, & Salas-Salvado, 2013; M. Li, McCulloch, & McDermott, 2012; Mozaffarian et al., 2015; Zhao et al., 2014).

The relationship between metabolic syndrome and mortality risk remains unclear, with some data indicating that metabolic syndrome increases all-cause and/or CVD mortality risk, and other data suggesting no increase in risk (Church et al., 2009; Mottillo et al., 2010; Mozaffarian, Kamineni, Prineas, & Siscovick, 2008). A meta-analysis by Mottillo et al. indicated that metabolic syndrome increased all-cause mortality by 58% (Mottillo et al., 2010). However, other research among older individuals (mean age 73 years) suggests that, while metabolic syndrome may correspond with a 22% greater all-cause mortality risk, this increased risk is likely driven by elevated fasting glucose and HTN (Mozaffarian et al., 2008). Indeed, only older individuals with metabolic syndrome who had elevated fasting glucose or HTN

demonstrated higher all-cause mortality (relative risk (RR): 1.41 and 1.26, respectively) (Mozaffarian et al., 2008). Mottillo et al.'s meta-analysis similarly found that metabolic syndrome did not increase all-cause mortality risk among individuals without DM; however, their study did not examine the unique contribution of individual metabolic syndrome components on all-cause mortality risk (Mottillo et al., 2010). Therefore, metabolic syndrome may increase all-cause mortality risk; however, the individual risk factors of elevated fasting glucose and HTN may drive the relationship between metabolic syndrome and all-cause mortality.

Metabolic syndrome also increases CVD mortality risk, with RR estimates ranging from 1.51 to 2.40 (Mottillo et al., 2010; Mozaffarian et al., 2008). Similar to overall mortality, individuals with metabolic syndrome who also have DM experience increased CVD mortality risk (HR 2.1 and 1.8 among individuals with and without DM, respectively) (Church et al., 2009). Higher CVD mortality risk also only occurs among individuals with metabolic syndrome who have either elevated fasting glucose and/or HTN (population attributable risk fraction (PAF): 9.6% and 11.3%, respectively) versus those without elevated fasting glucose or HTN (PAF: 1.1% and 0.2%, respectively) (Mozaffarian et al., 2008). These findings suggest the need to examine the presence of specific metabolic syndrome components when attempting to understand the relationship between metabolic syndrome and mortality risk.

Finally, some data suggest that the combined presence of DM and metabolic syndrome significantly increases the risk of CVD mortality among males when compared to the presence of metabolic syndrome alone, even after adjusting for CVD history (HR: 3.1 and 1.7, respectively) (Church et al., 2009). In contrast, among males with DM, the addition of metabolic syndrome did not significantly increase CVD mortality rate or the risk of CVD mortality (Church et al., 2009). This finding corresponds with other research suggesting that the presence of elevated fasting blood glucose (as represented by DM) may be the driving factor behind elevated CVD mortality among individuals with metabolic syndrome (Church et al., 2009; Mozaffarian et al., 2015).

While data regarding the effect of metabolic syndrome on all-cause and CVD-mortality remain mixed, more consistent research indicates that metabolic syndrome increases the risk for CVD, MI, and

stroke (RR: 2.35, 1.99, and 2.27, respectively), and these relationships existed even in the absence of DM (Mottillo et al., 2010). The INTERHEART study also found that metabolic syndrome increases the risk of MI, with the PAF ranging from 14.5% to 16.8%, depending on the definition of metabolic syndrome (Mente et al., 2010; Mozaffarian et al., 2015). Metabolic syndrome increases CVD risk even after adjusting for individual metabolic syndrome components (RR: 1.54) (Gami et al., 2007; Mozaffarian et al., 2015), and exhibiting a larger number of metabolic syndrome components further increases CVD risk (Mozaffarian et al., 2015; Wannamethee, Shaper, Lennon, & Morris, 2005). Specifically, the hazards ratios for CVD were 1.48 and 3.39 for males and females with 1 or 2 metabolic syndrome components versus 3.99 and 5.95 for males and females with ≥3 components, respectively (Mozaffarian et al., 2015; Wannamethee et al., 2005). Metabolic syndrome-related CVD risk also varies based on the clustering of risk factors present, with a combination of central obesity, elevated fasting glucose, and HTN conferring the greatest CVD risk (HR: 2.36) (Franco et al., 2009; Mozaffarian et al., 2015).

Considering the negative health consequences of metabolic syndrome, it is unsurprising that it increases health-care costs by ~24% for each additional metabolic syndrome component present (Boudreau et al., 2009; Mozaffarian et al., 2015). However, limited data exist to-date examining the precise direct and indirect medical costs associated with metabolic syndrome, or the DALYs associated with metabolic syndrome (Mozaffarian et al., 2015). Considering the substantial overlap between metabolic syndrome, CVD, and DM, it is reasonable to assume that metabolic syndrome accounts for substantial direct and indirect costs, as well as DALYs.

Metabolic syndrome, DM, and CVD negatively affect individuals and society due to their associated health, financial, social burdens. Reducing the burdens associated with these diseases requires a clear understanding of the behaviors that predict the development, progression, and health outcomes associated with these largely preventable chronic diseases.

Health Behaviors

The WHO states that “Most cardiovascular diseases can be prevented by addressing behavioral risk factors such as tobacco use, unhealthy diet and obesity, physical inactivity and harmful use of

alcohol" (World Health Organization, 2013). Indeed, estimates suggest that overweight/obesity and insufficient PA were responsible for 1 in 10 deaths in 2005 (Danaei et al., 2009; Mozaffarian et al., 2015), and 44% of the decrease in CHD-related deaths in the U.S. from 1980-2000 were due to changes in health behaviors and environmental-related risk factors (Ford et al., 2007; Mozaffarian et al., 2015). Research also consistently indicates that PA and maintaining a healthy weight are as robust predictors of CVD-related outcomes as traditional risk factors, like cholesterol, blood pressure, and DM (Despres, 2016; Folsom et al., 2011; Ford, Greenlund, & Hong, 2012; Lachman et al., 2016; Wu et al., 2012). Similar to CVD, the incidence, prevalence, and severity of DM and metabolic syndrome are largely related to health behaviors, with prevalence increasing as a result of greater long-term exposure to unhealthy behaviors, including physical inactivity, sedentary behavior, and screen time (Mozaffarian et al., 2015). Overall, research supports the significant role of health behaviors in predicting the onset, severity, and progression of diseases like CVD, DM, and metabolic syndrome.

Despite consistent associations between health behaviors and chronic disease, medical spending patterns reflect the U.S. health care system's penchant towards treating disease and injury, rather than preventing them by focusing on improving health behaviors (American Heart Association, 2017). Shifting the health care system towards prioritizing prevention over treatment represents a potentially feasible approach for reducing healthcare costs and promoting patients' well-being, lifespan, and quality of life (American Heart Association, 2017). Jean-Pierre Despres' stated that, "if behaviors are that important to cardiovascular health, they should be assessed and targeted in clinical practice" (Despres, 2016)(p. 510); however, shifting the health care system towards prioritizing prevention over treatment requires more than a basic knowledge regarding which health behaviors to target. Rather, such a philosophical shift requires a nuanced understanding of the extent to which specific health behaviors can effectively prevent or treat chronic disease. Targeting health behaviors also requires researchers to determine the proper 'dose' of a health behavior for promoting clinically meaningful health outcomes. Failure to identify the proper dose prevents clinicians and public health practitioners from communicating with patients regarding how much the patient needs to change a particular health behavior to experience meaningful

changes in disease risk or comorbidities. Determining the proper 'dose' of specific health behaviors, and identifying how this dose may differ based on an individual's unmodifiable characteristics (i.e. sex, race, etc.), requires researchers to expand beyond descriptive statistics and correlations into statistical models capable of accounting for unmodifiable characteristics, as well as between- and within-person variability in health behaviors and associated health outcomes. Data scientists are capable of combining appropriate statistical models with substantive expertise regarding the relationship between health behaviors and health outcomes. As such, data scientists may be able to help determine the appropriate dose of a health behavior for an individual, thereby providing essential information for clinicians that could support shifting from a focus on treatment towards a focus on prevention. Understanding the theoretical underpinnings of the relationship between health behaviors and chronic disease represents a necessary first step for data scientists attempting to shift the health care system towards a focus on prevention.

Weight Status

Research indicates that weight status, physical activity and inactivity, sedentary behavior, and sleep represent distinct health behaviors associated with chronic disease risk and health outcomes. Weight status also reflects an individual's genetics. While many other health behaviors, such as diet and tobacco use, also predict disease risk, this research focuses on examining the roles of weight status, physical activity and inactivity, sedentary behavior, and sleep in affecting chronic disease risk.

Weight status represents a unique predictor of chronic disease risk that reflects an individual's health behaviors and their genetics. While genetics are not modifiable, health behaviors are modifiable. Therefore, considering the strong link between weight status and health behaviors, it makes conceptual sense to examine weight status as a health behavior that affects health outcomes.

The CDC defines overweight and obesity as having a "weight that is higher than what is considered as a healthy weight for a given height" (Centers for Disease Control and Prevention, 2017b). This definition reflects the assumption that, at a given height, a higher weight means increased fatness (Flegal et al., 2009), and corresponds with the CDC's reliance on body mass index (BMI) as a screening tool to identify overweight/obesity, since BMI reflects an individual's weight-to-height ratio [weight

(kg)/height (m^2)] (Centers for Disease Control and Prevention, 2017b). The CDC uses BMI to screen for overweight/obesity because it typically correlates with body fatness, and is an appropriate tool for estimating the prevalence of overweight/obesity at the population-level (Centers for Disease Control and Prevention, 2017b). However, BMI may not always correlate with body fatness at the individual level, particularly among certain racial/ethnic groups, nor does it always accurately reflect an individual's disease risk, a short-coming that the CDC acknowledges (Centers for Disease Control and Prevention, 2017b). BMI also fails to account for sex (except in children), race/ethnicity, lean versus fat mass, and frame size, all short-comings researchers should recognize when using BMI to measure of weight status.

Despite these short-comings, several studies suggest that BMI provides similar estimates of disease risk to waist circumference (WC) and waist-to-hip (WHR) (Dalton et al., 2003; Flegal et al., 2009; R. Huxley, Mendis, Zheleznyakov, Reddy, & Chan, 2010). For example, the Asia Pacific Cohort Studies Collaboration (R. Huxley et al., 2010) found no clear differences in the associations between BMI, WC, and WHR and CVD risk or stroke outcomes (Asia Pacific Cohort Studies, 2006). Two meta-analyses found little difference in the strength of the association between BMI, WC, and WHR with DM risk, and all three measures performed equally well in identifying incident DM risk (Decoda Study Group et al., 2008; R. Huxley et al., 2010; Vazquez, Duval, Jacobs, & Silventoinen, 2007). BMI, WC, and WHR also perform equally well in identifying individuals with HTN and dyslipidemia (Decoda Study Group et al., 2008; R. Huxley et al., 2008; R. Huxley et al., 2010), and provide similar estimates of body fatness, with all three measures strongly correlating with percent body fat, total fat mass, and subcutaneous adipose tissue and moderately correlating with visceral adipose tissue (VAT) (Barreira et al., 2012; Flegal et al., 2009). While the literature provides no clear consensus regarding whether WC, WHR, or BMI provide similar predictive value regarding chronic disease risk or adiposity, this could be due to inter-individual variability in percent body fat at a given BMI, particularly among different racial/ethnic groups.

For example, Asian populations exhibit significant variation in the association between adiposity and BMI (Deurenberg, Deurenberg-Yap, & Guricci, 2002; R. Huxley et al., 2010), with some Asian populations having lower BMI's at a given percent of body fat compared with Europeans (R. Huxley et

al., 2010). Asians typically have 3-5% higher total body fat compared to Europeans with the same BMI (Deurenberg et al., 2002). However, Asians also differ from one another regarding the relationship between BMI and percent body fat, suggesting they should not be lumped into a single 'Asian' category (Deurenberg et al., 2002). Racial/ethnic differences may also exist for the association between BMI and health outcomes, with one study finding that Chinese individuals have stronger correlations between BMI and HTN than Caucasians, and non-Hispanic blacks have stronger correlations between BMI and HTN than Caucasians and Mexican Americans (Bell, Adair, & Popkin, 2002). These racial/ethnic differences in percent body fat at a given BMI, as well as the correlations between BMI and HTN, suggest the need for specific racial/ethnic cut-points for BMI categories. Racial/ethnic specific cut-points would remove one of the short-comings of BMI, increase its predictive utility, and reduce uncertainty about the relationship between BMI and health outcomes. Indeed, researchers have suggested racial/ethnic specific cut-points for BMI categories (Harvard School of Public Health, 2018).

Current BMI categories for a given weight status include: 1) BMI <18.5 kg/m^2 = Underweight; 2) BMI 18.5 – 24.9 kg/m^2 = Normal weight; 3) BMI 25.0 – 29.9 kg/m^2 = Overweight; and 4) BMI ≥ 30.0 kg/m^2 = Obese (Centers for Disease Control and Prevention, 2017b). However, Dobbelsteyn et al. found that the optimal BMI cut-points for identifying CVD risk depend upon sex, with cut-points of 25 – 26 kg/m^2 and 23 – 26 kg/m^2 for males and females, respectively (Dobbelsteyn, Joffres, MacLean, & Flowerdew, 2001). Dobbelsteyn et al. did not examine race/ethnicity, and many researchers express concern regarding the continued use of BMI cut-points that fail to account for race/ethnicity. Researchers advocating for racial/ethnic specific cut-points suggest that China and Japan define overweight and obese as a BMI 24.0 – 27.9 kg/m^2 and a BMI ≥ 28.0 kg/m^2, respectively, and that India defines overweight and obese as a BMI 23.0 – 26.9 kg/m^2 and a BMI ≥ 27.0 kg/m^2, respectively (Harvard School of Public Health, 2018). Less debate exists regarding the need for sex-specific BMI cut-points, though they may be worth considering (Dobbelsteyn et al., 2001).

In contrast to adult values, BMI values in children are standardized to provide sex-specific BMI-for-age z-scores (Centers for Disease Control and Prevention, 2017b). BMI-for-age z-scores categorize

children's weight status based on their percentile on the CDC growth charts, with categories including underweight (BMI < 5th percentile), normal weight (BMI 5th to < 85th percentile), overweight (BMI 85th to < 95th percentile), and obese (BMI ≥ 95th percentile) (Centers for Disease Control and Prevention, 2017b). These sex-specific BMI-for-age z-scores eliminate the failure to account for sex when using BMI in adults. However, similar to adults, there are no racial/ethnic specific BMI cut-points in children, and debate regarding the utility of racial/ethnic specific cut-points continues.

Given the utility of BMI for providing population-level estimates of overweight/obesity, prevalence rates are typically based on BMI. The U.S. exhibits substantially high obesity prevalence rates, with 2015-2016 NHANES data suggesting that 39.8% of US adults ages 20 years and older are obese (Hales, Carroll, Fryar, & Ogden, 2017). Additionally, 18.5% of children and adolescent are obese (Hales et al., 2017). Global obesity rates are also high, with 39% and 13% of adults ≥18 years of age being overweight or obese, respectively (World Health Organization, 2018). As of 2016, over 340 million children/adolescents aged 5-19 years old and 41 million children <5 years old were overweight or obese (World Health Organization, 2018). The high prevalence of overweight/obesity is concerning because it suggests that adults and children may be at high risk for chronic disease and mortality.

Obesity accounts for more than 400,000 total deaths annually (Dufour, 2018), and being overweight or obese decreases life expectancy by one or three years, respectively (Dufour, 2018). The HRs for all-cause mortality are 1.07, 1.41, and 2.46, among overweight, obese, and extremely obese individuals, respectively (Ma, Flanders, Ward, & Jemal, 2011; Mozaffarian et al., 2015), though some data suggest that all-cause mortality risk does not increase among overweight individuals (Flegal, Graubard, Williamson, & Gail, 2005; Flegal, Kit, Orpana, & Graubard, 2013; McGee & Diverse Populations Collaboration, 2005; Mozaffarian et al., 2015). Prospective research suggests that overall mortality rates are lowest among individuals with a BMI between 22.5 and 25 kg/m^2, implying that having too low of a BMI may increase mortality risk (Mozaffarian et al., 2015; Prospective Studies et al., 2009). While the effects of having a BMI between 18.5 and 30.0 kg/m^2 on mortality risk remains unclear, having a BMI ≥30 kg/m^2 consistently predicts greater mortality risk (Mozaffarian et al., 2015).

Being overweight or obese also increases the risk for CVD-related morbidities, and obesity increases the risk for CVD, DM, and metabolic syndrome in adults (Mozaffarian et al., 2015). Compared to normal weight individuals, overweight and obese individuals have higher odds of developing metabolic syndrome (OR: 2.81 and 5.24, respectively) (Cheriyath, Duan, Qian, Nambiar, & Liao, 2010; Mozaffarian et al., 2015). Obesity correlates with subclinical measures of atherosclerosis, including coronary artery calcium and carotid intima-media thickness (Burke et al., 2008; Mozaffarian et al., 2015). Overweight and obese individuals also have an increased risk for ischemic stroke (RR: 1.22 and 1.64, respectively) and hemorrhagic stroke (RR: 1.01 and 1.24, respectively) (Mozaffarian et al., 2015; Strazzullo et al., 2010). The increased risks associated with overweight and obesity extend beyond those listed above, affecting risk for anxiety, depression, and Alzheimer's (Mozaffarian et al., 2015). However, one important consideration when examining the relationship between obesity and CVD is the so-called 'obesity paradox'. This 'paradox' refers to evidence indicating that overweight and obese individuals with CVD have a better prognosis than normal weight individuals with the same CVD (Myers et al., 2015).

This paradox could be due to the distribution of body fat. Indeed, in the 1940s, French physician Jean Vague suggested that the relationship between adiposity and health may be more closely related to body fat distribution (e.g. abdominal fat (VAT) vs thigh/hip fat) than to excess adiposity (Myers et al., 2015). Technological advances have allowed an in-depth understanding of the role of VAT in predicting metabolic health and CVD risk. For example, computerized tomography scans indicate that only excess VAT, not overall excess adiposity, correlates with glucose intolerance and dyslipidemia (Myers et al., 2015). VAT also correlates with greater insulin resistance, glucose intolerance, DM, and dyslipidemia, regardless of BMI or total adiposity (Myers et al., 2015). This consistently strong relationship between VAT and health outcomes has caused multiple researchers to suggest that reducing VAT may be more important than reducing overall adiposity (Despres, 2012; Myers et al., 2015; Ross & Bradshaw, 2009).

The metabolic characteristics of VAT help explain the physiological mechanisms underlying the relationship between VAT, insulin resistance, and dyslipidemia. VAT exhibits high levels of lipolysis, which increases the concentration of free fatty acids in the serum, thereby exposing the liver and other

tissues to high free fatty acid concentrations (Myers et al., 2015; J. D. Smith et al., 2012), and VAT resists the anti-lipolytic action of insulin (Myers et al., 2015; J. D. Smith et al., 2012). Exposing the liver to high free fatty acid concentrations impairs liver metabolism, which increases the production of triglyceride-rich lipoproteins and glucose output, ultimately contributing to hyperglycemia (Despres et al., 1990; Myers et al., 2015). VAT is also characterized by high concentrations of macrophages, making it pro-inflammatory (Myers et al., 2015; J. D. Smith et al., 2012). Along with these characteristics of VAT, some researchers suggest that excess VAT may relate to an individual's inability to use subcutaneous adipose tissue as a metabolic sink when exposed to excess caloric intake (Myers et al., 2015).

Under ideal circumstances, when an individual's caloric intake exceeds their needs, subcutaneous fat depots expand via hyperplasia (the creation of more fat cells) to provide an expanded metabolic reservoir for calories, thereby protecting lean tissues from accumulating harmful lipids (Myers et al., 2015). However, if an individual cannot expand their subcutaneous fat depots, the excess calories accumulate as VAT and ectopic fat, in which fat is distributed in normally lean tissues, such as the liver, heart, kidneys, and skeletal muscle (Despres et al., 2008; Myers et al., 2015). This fat distribution significantly affects health, with multiple studies indicating that larger ectopic fat depots negatively alter cardiometabolic risk profiles (Britton & Fox, 2011; Despres, 2012; Myers et al., 2015). Ectopic fat accumulation in the liver may could also be a key cause of hyperglycemia, hyperinsulinemia, and dyslipidemia (Despres et al., 2008; Myers et al., 2015), and ectopic fat accumulation in skeletal muscle may contribute to systemic insulin resistance (Myers et al., 2015; Samuel, Petersen, & Shulman, 2010). These metabolic characteristics of ectopic fat and VAT help explain the relationship between weight status and disease risk, as well as the roles of body fat distribution in explaining the 'obesity paradox'.

Genetics may also play a role in the relationship between increased adiposity and negative health outcomes. Specifically, Lu et al.'s meta-analysis indicated that twelve genetic loci correlate with increased overall adiposity, as assessed by BMI and percent body fat (Lu et al., 2016). They found seven loci that affected percent body fat more than BMI, and five that affected BMI more than percent body fat, suggesting that the seven loci associated with percent body fat primarily affect overall adiposity; whereas,

the five loci associated with BMI affect overall adiposity and lean mass (Lu et al., 2016). The loci associated with percent body fat also correlated with cardiometabolic outcomes, including increased circulating leptin, subcutaneous adipose tissue, VAT, LDL-cholesterol, triglycerides, insulin resistance, and C-reactive protein, as well as decreased HDL-cholesterol (Lu et al., 2016). These findings indicate that genetic factors affecting overall adiposity and fat/lean mass may also affect cardiometabolic outcomes, suggesting another potential link between weight status and health outcomes.

Not surprisingly, the negative health consequences of obesity are reflected by high medical costs. The U.S. spends $150-$190 billion annually on obesity (Dufour, 2018). Obese patients spend an additional $3615 per year on medical costs, and Medicare, Medicaid, and private insurers pay $1723, $1021, and $1140 more for obese beneficiaries than normal weight beneficiaries, respectively (Finkelstein, Trogdon, Cohen, & Dietz, 2009; Mozaffarian et al., 2015). Across their lifetimes, obese males and females spend almost $200,000 and $225,000 more on healthcare expenses than their normal weight counterparts, respectively (Dufour, 2018). These estimates represent direct medical costs; however, obesity also incurs substantial indirect costs, with obesity-related absenteeism costing $3.38 to $6.38 billion annually (Dufour, 2018). Finally, estimates suggest that employers spend an additional $506 per obese worker annually, due to increased sick days and medical claims (Dufour, 2018).

In summary, research consistently demonstrates that greater adiposity results in worse health outcomes, including increased risk for mortality, CVD-related morbidities, and risk for CVD, DM, and metabolic syndrome. The metabolic characteristics of VAT provide an explanation for the physiological mechanisms underlying the relationship between adiposity and disease risk. There are some short-comings associated with using BMI as a measure of weight status, and researchers should considering these limitations when designing research studies, modeling data, and interpreting outcomes. Considering consistent data indicating the importance of race/ethnicity regarding BMI, researchers using BMI as a measure of weight status would be wise to examine the potential moderating effect of race/ethnicity. Finally, other health behaviors, including physical activity/inactivity and sedentary behavior likely require consideration as potential moderators or mediators of the effect of adiposity on health outcomes.

Physical Activity and Inactivity

In recognition of the significant role PA plays in preventing CVD, the AHA selected PA as one of its seven components of ideal cardiovascular health (Lloyd-Jones et al., 2010; Mozaffarian et al., 2015). The CDC also recognizes the importance of adequate PA in promoting ideal health and sets public health guidelines, including specific PA recommendations for various age groups, such as preschool-aged children (3-5 years of age), children and adolescents (6-17 years of age), adults (18-64 years of age), and older adults (65 years and older), as well as for women during pregnancy and post-partum, and for adults with chronic health conditions and disabilities (U.S. Department of Health and Human Services, 2018). The guidelines for children and adolescents recommend at least 60 minutes of moderate-to-vigorous PA (MVPA) per day, emphasize aerobic activity, and suggest participating in muscle- and bone-strengthening activity at least three days per week (U.S. Department of Health and Human Services, 2018). The guidelines for adults emphasize the need to stand more and sit less, with guidelines recommending at least 150-300 minutes of moderate PA per week or 75-150 minutes of vigorous PA per week, or a combination thereof (U.S. Department of Health and Human Services, 2018). The CDC also recommends that adults spread their aerobic activity throughout the week and engage in moderate or vigorous intensity muscle-strengthening activities that involve all major muscle groups on at least two days per week (U.S. Department of Health and Human Services, 2018). Additional recommendations, particularly for those with disabilities, suggest focusing on activities a person is physically capable of and increasing the frequency and intensity of PA across time (U.S. Department of Health and Human Services, 2018). These recommendations focus on the key messages that: 1) Some PA is better than none – "Even minutes of physical activity has real health benefits ... [so] do what you can"; 2) Greater quantity and intensity of PA confers greater health benefits; and 3) PA should include aerobic and muscle-strengthening activities (U.S. Department of Health and Human Services, 2018). That small amounts of PA confer health benefits is important because individuals often identify time as their greatest barrier to PA participation (Myers et al., 2015). However, while some PA is better than none, one must also consider the detrimental effects of physical inactivity when attempting to understand the relationship between activity and chronic disease.

Physical inactivity refers to an individual failing to participate in sufficient PA to experience PA-related health benefits (Despres, 2016). As such, physical inactivity should be considered in tandem with PA.

Despite the strong public health focus on PA, few individuals achieve PA recommendations. For example, only 42% of children ages 6-11 years old and only 8% of adolescents meet PA recommendations (Troiano et al., 2008). Among adults aged 20 to 59 years of age, only 3.8% and 3.2% of males and females meet PA recommendations, respectively, with even lower rates among adults 60 years and older, among whom only 2.5% and 2.3% of males and females meet recommendations, respectively (Troiano et al., 2008). Global estimates indicate that 69% of adults meet PA recommendations (Kohl et al., 2012); however, these values may be inaccurate because they were based on self-report, which often results in over-estimating PA participation (Mozaffarian et al., 2015; Prince et al., 2008). Physical inactivity mirrors PA participation, with most individuals demonstrating high levels of inactivity. In the U.S., 15.2% of adolescents reported being inactive during the previous seven days, and more females than males reported being inactive (19.2% and 11.2%, respectively) (Kann et al., 2014; Mozaffarian et al., 2015). Adult inactivity levels are high and increase with age, with 25.1%, 32.8%, 35.7%, and 51.9% of adults ages 18 to 44 years, 45 to 64 years, 65 to 74 years, and 75 years or older reporting being inactive, respectively (Mozaffarian et al., 2015). Globally, 17% of adults reported being physically inactive in 2009 (Kohl et al., 2012). The high prevalence of physical inactivity paired with the low prevalence of individuals meeting PA recommendations causes concern, particularly since even small amounts of PA can reduce mortality and confer substantial health benefits (Despres, 2016; Lewis & Hennekens, 2016; Luke, Dugas, Durazo-Arvizu, Cao, & Cooper, 2011; Manson et al., 1999; Mozaffarian et al., 2015).

The health benefits associated with PA participation include improving CVD risk factors, such as HTN and cholesterol levels, and reducing the likelihood of CVD-related diseases, including CHD, stroke, DM, and acute MI (Mozaffarian et al., 2015). PA also reduces the risk for colon, breast, and pancreatic cancer; improves muscle, bone, and joint health, and helps individuals maintain physical functioning, thereby preserving the ability for adults, particularly older adults, to maintain independence (Lewis & Hennekens, 2016). These benefits occur among all individuals, regardless of age, sex, disease or disability

status, hence the CDC's recommendation for all individuals to engage in PA that corresponds with their physical fitness, abilities, etc. (Mozaffarian et al., 2015).

Small amounts of PA confer health benefits, with research suggesting that participating in as little as 3-10 minutes of moderate PA per day, or running slowly for 5-10 minutes per day, markedly reduces mortality risk (Myers et al., 2015). Walking at a brisk pace for 20 minutes per day also reduces MI risk by 30-40% (Lewis & Hennekens, 2016; Manson et al., 1999). Longitudinal data indicate that individuals who perform at least some leisure-time PA, even if they fail to meet PA recommendations, experience a 20% lower mortality risk compared to individuals who participate in no leisure-time PA (Arem et al., 2015; Despres, 2016). Other studies support the finding that individuals who participate in some PA, despite not meeting PA recommendations, experience reduced mortality risk compared to individuals who do not participate in PA (HR: 0.66) (Despres, 2016; Gebel et al., 2015).

Small amounts of PA participation also significantly affect CVD comorbidities and risk for DM and metabolic syndrome. NHANES data revealed significant negative associations between the number of minute-long moderate or vigorous PA bouts per day and adults' systolic blood pressure, blood glucose, HTN, and DM, and a significant positive association with HDL-cholesterol (Luke et al., 2011). They also found that overall activity counts per minute were negatively associated with plasma glucose, HTN, and DM, and were positively associated with HDL-cholesterol (Luke et al., 2011). Finally, each one standard deviation increase in activity counts per minute (SD: 4.3) or minute-long moderate or vigorous PA bouts per day (SD: 0.8) was associated with reduced odds for HTN (OR: 0.78 and 0.81, respectively) and DM (OR: 0.64 and 0.50, respectively) (Luke et al., 2011). As such, the evidence consistently suggests that even small amounts of PA participation can reduce the risk for mortality, CVD, CVD comorbidities, DM, and metabolic syndrome.

While small amounts of PA may confer health benefits, physical inactivity still negatively affects mortality risk, with global estimates suggesting that physical inactivity accounts for 6-10% of all deaths and for 30% of deaths due to ischemic heart disease (Kohl et al., 2012). Estimates suggest that eliminating physical inactivity globally would increase longevity by 0.68 years (DeFina et al., 2015; Lee et al., 2012),

and that, if physically inactive people participated in sufficient PA, 5.3-5.7 million global deaths could be prevented (Kohl et al., 2012). Research also consistently supports the positive effect of meeting PA recommendations on mortality risk (Arem et al., 2015; Despres, 2016; Gebel et al., 2015). For example, compared with individuals who participated in no leisure-time PA, those who performed 1-2 times or 2-3 times the recommended minimum experienced 31% and 37% lower mortality risk, respectively (Arem et al., 2015; Despres, 2016), and individuals who participated in 150-299 minutes or ≥300 minutes of PA per week experienced reduced mortality risk (HR: 0.53 and 0.46, respectively) (Despres, 2016; Gebel et al., 2015). Participating in high amounts of leisure-time PA also lowers risk for incident CVD compared to participating in low amounts of leisure-time PA (RR: 0.76 in males and 0.73 in females), and researchers estimate that a high level of leisure-time PA could reduce the overall risk of incident CHD and stroke among males and females by 20-30% and 10-20%, respectively (J. Li & Siegrist, 2012).

Sufficient PA participation reduces the risk for DM and metabolic syndrome and, among adults at-risk for DM, those who achieved the recommended 150 minutes of PA per week were 44% less likely to develop DM at 3.5 years follow-up (Hamman et al., 2006; Mozaffarian et al., 2015). Achieving 120-150 minutes per week of moderate-intensity PA also reduces the risk of developing metabolic syndrome (Mozaffarian et al., 2015; U.S. Department of Health and Human Services, 2018). Compared with individuals in the lowest quartile of leisure-time PA, individuals in the highest and middle quartiles of leisure-time PA experience reduced odds for developing metabolic syndrome (OR: 0.80 and 0.92, respectively) (DeFina et al., 2015; He et al., 2014; Mozaffarian et al., 2015). Additionally, among individuals with DM, metabolic syndrome, or abdominal obesity, those who are very physically active experience a 50% decreased CVD risk compared to those who are physically inactive (Broekhuizen et al., 2011; Myers et al., 2015). Indeed, physical inactivity is considered a leading contributor to premature morbidity in the U.S., accounting for 22% of CHD, 12% of DM, and 12% of HTN, among other things (Lewis & Hennekens, 2016), and Lee et al. found that eliminating physical inactivity globally would eliminate 5.8% of CHD (Lee et al., 2012).

Not only does physical inactivity directly affect morbidity and mortality, habitual physical inactivity may mediate the relationship between obesity and CVD risk, and physical inactivity and obesity synergistically increase CVD risk (Myers et al., 2015). The Nurse's Health Study revealed that inactive obese females experienced a 62% higher CVD mortality rate compared to active obese females (Myers et al., 2015). Other studies found that, compared to active obese males and females, inactive obese males and females were 45% and 90% more likely to die from CVD, respectively (Myers et al., 2015). Multiple studies indicate that physically inactive individuals experience substantially higher obesity-associated CVD risk (~35-90%) compared to physically active obese individuals (Myers et al., 2015). In contrast, PA participation improves health outcomes and reduces mortality risk, even in the absence of weight loss (Despres, 2012; Myers et al., 2015), suggesting that sufficient PA participation may ameliorate some of the negative effects of excess adiposity on morbidity and mortality, whereas physical inactivity potentially exacerbates these effects.

The physiological mechanisms underlying the mediating effect of physical inactivity on obesity and CVD risk remain poorly understood; however, the negative effects of physical inactivity on insulin resistance and abdominal obesity may provide some explanation. Physically inactive obese individuals have 88% higher odds for insulin resistance than those who are physically active (Myers et al., 2015). Additionally, physically inactive males and females with abdominal obesity experience a 27% and 10% higher likelihood of developing CHD, respectively, than do their active counterparts (Myers et al., 2015). These findings align with other literature suggesting that the distribution of fat accumulation may be more important in determining CVD, DM, and metabolic syndrome risk than total fat mass or body fat percentage (Despres, 2012; Myers et al., 2015; Ross & Bradshaw, 2009).

While the physiological mechanisms underlying the relationship between physical inactivity, obesity, and CVD risk require additional investigation, the mechanisms underlying the positive effects of PA on obesity-related CVD mortality are more readily understood (Myers et al., 2015). Regular PA mobilizes VAT and ectopic fat depots, thus ameliorating the negative effects of these fat depots on health (Despres, 2012; Myers et al., 2015; Ross & Bradshaw, 2009). Skeletal muscle contractions accompanying

PA may also increase lipoprotein lipase activity, thereby positively affecting triglyceride levels and potentially reducing CVD risk (Brocklebank, Falconer, Page, Perry, & Cooper, 2015). Greater PA participation typically correlates with more favorable cardiac structure and function (Myers et al., 2015). PA-related skeletal muscle contractions may increase muscle-contraction-stimulated GLUT-4 translocation to the cell membrane (Despres, 2016; Hamilton, Hamilton, & Zderic, 2004), thus improving cells' ability to uptake glucose, thereby positively affecting insulin sensitivity and the risk for DM or metabolic syndrome (Brocklebank et al., 2015). Finally, skeletal muscle contractions turn on gene expression associated with proper insulin sensitivity, which may reduce risk for DM and metabolic syndrome (Despres, 2016; Hamilton et al., 2004). These beneficial physiological effects of PA help explain how PA reduces the risk for CVD, DM, and metabolic syndrome.

In summary, research consistently demonstrates that, while participating in any amount of PA confers positive health benefits, physical inactivity is detrimental to health, and participating in greater amounts of PA and/or achieving PA recommendations results in better health outcomes. While the physiological mechanisms underlying the relationship between physical inactivity, obesity, and CVD-risk require additional investigation, the mechanisms underlying the positive effects of PA on CVD, DM, and metabolic risk are better understood. The differential effects of PA and inactivity on chronic disease risk suggest that researchers may want to simultaneously examine PA and physical inactivity in statistical models, and may want to execute separate models using continuous or categorical variables (meeting vs. not meeting PA recommendations) to tease out these unique effects. Examining these effects separately or in combination may help researchers disentangle the effects of overall quantity of PA, physical inactivity, and meeting/not meeting PA recommendations on health outcomes.

Sedentary Behavior

Sedentary behavior (SB) represent a distinct construct from physical activity/inactivity that is characterized by waking behaviors that occur while sitting or reclining and which require minimal energy expenditure (≤1.5 METS) (Barnes et al., 2012; Brocklebank et al., 2015; Despres, 2016). Researchers often capture SB via measures of sitting, lying, or screen time (television viewing, computer use, etc.)

(Barnes et al., 2012; Brocklebank et al., 2015; Despres, 2016); however, more recent studies use accelerometers as an objective measure of SB (Brocklebank et al., 2015). The specific method used to measure SB requires careful consideration, as research suggests that measuring SB via accelerometers may be conceptually different than measuring SB via self-report (Saunders et al., 2013). For example, researchers using screen time as a proxy for SB found a positive correlation with food intake; however, screen time consisted of watching television or playing video games, suggesting that this relationship between screen time (SB) and increase food intake may be limited to those specific measures of screen time (Chaput et al., 2011; J. L. Harris, Bargh, & Brownell, 2009; Saunders et al., 2013). Therefore, researchers should consider the method used for measuring SB, since the measure used affects the interpretation of the relationship between SB and health outcomes (Chaput et al., 2011; J. L. Harris et al., 2009; Saunders et al., 2013). Indeed, Saunders et al. found that self-reported measures of SB in children and adolescents were more consistently associated with health risk than accelerometer-based measures of SB, reinforcing the idea that accelerometer versus self-report SB measures may represent different constructs (Saunders et al., 2013). As such, researchers should be cautious when interpreting the effects of self-reported SB, particularly as represented via screen time, on health outcomes.

The prevalence of SB among U.S. adults and adolescents is high, and 41.3% of adolescents report using computers for at least three hours per day and 32.5% report watching television for at least three hours per day (Kann et al., 2014; Mozaffarian et al., 2015). Accelerometer data suggest that U.S. children spend 6.07 to 8.03 hours/day in SB (6-11 versus 16-19 year olds, respectively) (Matthews et al., 2008). U.S. adults spend an average of 8.44 hours per day in SB (Healy, Matthews, Dunstan, Winkler, & Owen, 2011), and among adults 20 years and older, time spent in SB ranges from 7.48 to 9.28 hours/day, depending on the age group (20-29 vs. 70-85 year olds) (Matthews et al., 2008). Although individuals spend a large amount of time in SB, an individual's SB may not be sustained for extended time periods, as research suggests that sedentary time is typically interrupted 92.5 times per day, with breaks lasting 4.12 minutes (Healy et al., 2011).

The large proportion of time individuals spend in SB is concerning, particularly when considering the negative health effects of SB, which occur independently from PA participation (Biswas et al., 2015; Chau et al., 2013; Despres, 2016; Katzmarzyk, Church, Craig, & Bouchard, 2009). Time spent in SB consistently correlates with increased risk for all-cause, CVD-related, and other causes of mortality, and the effects of SB are independent of BMI and PA participation (Biswas et al., 2015; Chau et al., 2013; Despres, 2016; Katzmarzyk et al., 2009; Matthews et al., 2014; Thorp, Owen, Neuhaus, & Dunstan, 2011). SB also affects morbidity, even after adjusting for PA (Biswas et al., 2015; Chau et al., 2013; Despres, 2016; Katzmarzyk et al., 2009). SB significantly predicts CVD incidence (Thorp et al., 2011) and the risk for CVD and stroke (Mozaffarian et al., 2015). Total time spent in SB correlates unfavorably with insulin sensitivity, fasting insulin, and triglycerides, even after adjusting for MVPA (Brocklebank et al., 2015). However, the relationships between SB and 2-hour plasma glucose, HDL-cholesterol, fasting plasma glucose, total cholesterol, and LDL-cholesterol remain inconclusive (Brocklebank et al., 2015). Finally, some data indicate that that high levels of SB increase risk for DM and some cancers (i.e. ovarian, colon, and endometrial cancer), as well as incidence of mental disorders (Thorp et al., 2011). Breaks in SB throughout the day may affect the relationship between SB and health outcomes, with a greater number of breaks correlating with lower triglyceride levels, even after adjusting for MVPA and total sedentary time (Brocklebank et al., 2015). However, research regarding the cross-sectional associations between breaks in SB and other cardiometabolic outcomes, such as insulin sensitivity and HDL-cholesterol, remains inconclusive (Brocklebank et al., 2015). Generally speaking, research to-date supports the existence of cross-sectional relationships between SB, mortality, and morbidities, and some data suggest that breaks in SB may correlate with health outcomes; however we need additional research to fully elucidate the relationship between SB, breaks in SB, and health outcomes.

Some longitudinal data support the role of SB in predicting health outcomes. Chau et al. and Chastin et al. conducted meta-analyses examining the relationship between SB (conceptualized as time spent sitting or breaks in SB, respectively) and health outcomes (Chastin, Egerton, Leask, & Stamatakis, 2015; Chau et al., 2013). Chau et al. found that progressive increases in time spent sitting predicted a

higher hazard ratio for all-cause mortality, even after adjusting for PA participation (Chau et al., 2013). They estimated that, based on the dose-response relationship between sitting time and mortality, spending 10 hours/day sitting increases all-cause mortality risk by 34% and 52% with and without adjusting for PA, respectively (Chau et al., 2013). They also estimated that, after controlling for PA participation, time spent sitting accounted for 5.9% of the PAF for all-cause mortality (Chau et al., 2013). Chastin et al. found that breaks in SB characterized by standing significantly affected insulin levels, but not blood glucose levels (Chastin et al., 2015). In contrast, breaks in SB characterized by light PA or MVPA significantly predicted decreased postprandial blood glucose responses (-17.42% and -1.40%, respectively) and reduced postprandial insulin levels (-14.92% and -23.84%, respectively) (Chastin et al., 2015). Regardless of whether breaks were characterized by standing, light PA, or MVPA, breaks in SB did not affect triglycerides or C-peptides (Chastin et al., 2015). These longitudinal data provide some support for the idea that SB (time spent sitting) and breaks in SB predict mortality and cardiometabolic health outcomes; however, additional longitudinal research is needed to better characterize SB and breaks in SB as predictors of mortality and cardiometabolic health outcomes.

Although SB independently correlates with and predicts mortality and cardiometabolic health outcomes, variables like weight status may modify these relationships. For example, some research suggests that weight status moderates the relationship between SB and risk for DM and cancer (Thorp et al., 2011). However, the relationship between SB and weight status is somewhat complex. For example, substantial evidence indicates that greater time spent in SB increases long-term obesity risk, though baseline BMI may moderate this relationship (Thorp et al., 2011). Greater SB also positively correlates with weight gain, even after controlling for PA participation (Thorp et al., 2011). Perhaps most importantly, greater SB during childhood or adolescence consistently predicts obesity prevalence and a higher BMI in adulthood independent of childhood/adolescent BMI or time spent in PA (Thorp et al., 2011). SB in childhood/adolescence may affect weight status in adulthood, and weight status may moderate the relationship between SB and chronic disease; however, additional research examining the potential moderating effect of weight status on SB and chronic disease risk is needed.

PA is another potential moderator of the effects of SB on health outcomes, weight status, and weight gain. Contrary to what one might suppose, PA participation does not attenuate or moderate the relationship between SB and risk of overweight/obesity or weight gain (Thorp et al., 2011). However, PA may moderate the relationship between SB and health outcomes, with some data suggesting that meeting PA guidelines ameliorates the detrimental effects of SB on health outcomes (Biswas et al., 2015; Despres, 2016); whereas, other data suggest that PA does not significantly modify the relationship between SB and the risk of mortality, DM, HTN, or ovarian cancer (Thorp et al., 2011). Researchers may be well-advised to consider SB, weight status, and PA as separate constructs in analyses attempting to disentangle the unique and combined effects of these variables on health outcomes.

The physiological mechanisms through which SB affects cardiometabolic health outcomes are not fully specified, though these mechanisms likely overlap with those related to physical inactivity (Despres, 2016; Lavie et al., 2015). When considering weight status, research suggests that prolonged SB may promote VAT or ectopic fat accumulation, leading to HTN, dyslipidemia, and other negative cardiometabolic outcomes (Despres, 2016; Henson et al., 2015). Additionally, the lack of skeletal muscle activation that accompanies SB may reduce lipoprotein lipase activity, thereby negatively affecting triglyceride levels (Brocklebank et al., 2015; Despres, 2016; Hamilton et al., 2004). Lack of skeletal muscle activation may also reduce muscle-contraction-stimulated GLUT-4 translocation, thus reducing cells' ability to uptake glucose and decreasing insulin sensitivity (Brocklebank et al., 2015). Finally, a lack of skeletal muscle activation could turn off gene expression associated with proper insulin sensitivity (Despres, 2016; Hamilton et al., 2004). When considering the physiological effects of breaks in SB, the lack of significant associations with many cardiometabolic health outcomes could be due to the fact that breaks, particularly those characterized by standing or light PA, may be insufficient to counteract the acute negative effects of SB on cardiometabolic health (Chastin et al., 2015). The short time span over which individuals are studied may also explain these findings, because they do not capture the long-term effects of breaks in SB on health outcomes. For example, some data suggest that breaks in SB may affect

gene-expression related to glucose metabolism, a carry-over effect that would not be captured via cross-sectional studies or studies with short-term follow-up (Chastin et al., 2015; Latouche et al., 2013).

Research to-date supports the negative effects of SB on mortality and cardiometabolic health outcomes, independent of PA, and some data supports breaks in SB as a means to ameliorate the negative effects of SB. Unfortunately, the majority of studies are cross-sectional or rely on self-reported measures of SB; therefore, additional longitudinal studies using objective measures of SB are needed. Finally, we need more research examining the effect of breaks in SB on cardiometabolic health outcomes. Such studies should examine the effects of the frequency, number, duration, and intensity level of breaks in SB on health outcomes (Chastin et al., 2015). The finding that breaks in SB characterized by standing rarely affect cardiometabolic health outcomes reinforces the need for said research because, if breaks alone were sufficient to promote better cardiometabolic health outcomes, then one would expect that breaks characterized by standing would promote similar changes in cardiometabolic health outcomes as would those characterized by light PA or MVPA (Chastin et al., 2015). Expanding SB research based on the suggestions above could help inform clinicians and public health practitioners regarding recommendations related to SB.

The CDC currently recommends that "adults should move more and sit less" (U.S. Department of Health and Human Services, 2018), a recommendation supported by the literature to-date. However, without additional research examining the role of breaks in SB, as well as the potential moderating effects of weight status and PA on health outcomes, recommendations will remain vague. Such recommendations may be appropriate at the population level, but may be insufficient to help individuals engage in positive health behavior changes. Researchers attempting to understand how these variables interact to affect health outcomes will benefit from collaborating with data scientists whose statistical skills are well-suited to pursue a nuanced understanding of these complex relationships.

Sleep

Sleep represents another important behavior to consider when examining health outcomes, particularly since humans spend about 30% of their time sleeping (Wolk, Gami, Garcia-Touchard, &

Somers, 2005). While physiological rest constitutes the primary role of sleep, sleep also affects cardiovascular homeostasis (Wolk et al., 2005). Patterns of cardiovascular homeostasis follow a 24-hour cycle that corresponds with changes in autonomic nervous system activity, with increased parasympathetic activity during sleep corresponding with the lowest heart rate and blood pressure levels throughout a 24-hour cycle (Wolk et al., 2005). While sleep corresponds with lower heart rate and blood pressure, bursts of sympathetic nerve activity during the rapid eye movement stage of sleep change muscle tone, increase heart rate, and increase blood pressure to levels similar to those seen during wakefulness (Wolk et al., 2005). Sleep also affects cardiovascular homeostasis due to changes in arrhythmias, conduction disturbances, sinus pauses, vascular tone, endothelial function, catecholamine levels, and shear stress, and these sleep-related changes in cardiovascular homeostasis occur in healthy and unhealthy individuals (Wolk et al., 2005). In contrast with greater parasympathetic activity during sleep, the early morning and waking period corresponds with increased sympathetic activity resulting in increased heart rate, blood pressure, and vasomotor tone in the coronary arteries (Wolk et al., 2005). The early morning is also characterized by decreased endothelial function and increased blood coagulability due to greater platelet aggregation, blood viscosity, etc., changes which may explain the peak in the occurrence of CVD and cerebrovascular events during the morning (Wolk et al., 2005). These typical changes in cardiovascular homeostasis throughout the 24-hour period help maintain cardiovascular health. Disturbing cardiovascular homeostasis, particularly by disrupting normal sleep, significantly influences the cardiovascular system and may predict the development of CVD in otherwise healthy individuals (Wolk et al., 2005).

A large body of research supports the relationship between sleep and CVD, with research consistently indicating that sleep duration, acute sleep deprivation, and accumulated sleep debt correlate with the risk for CVD and metabolic disease (Heslop, Smith, Metcalfe, Macleod, & Hart, 2002a, 2002b; Kashani, Eliasson, & Vernalis, 2012; Wolk et al., 2005). These variables also predict health outcomes, with chronic episodes of short sleep duration and sleep deprivation predicting increased risk for coronary events, DM, HTN, and mortality (Heslop et al., 2002a, 2002b; Kashani et al., 2012; Wolk et al., 2005).

The effects of sleep on health outcomes are particularly well-characterized in shift workers, whose work schedules strongly increase their odds of experiencing sleep deprivation, greater sleep debt, and other sleep disturbances (Akerstedt, Fredlund, Gillberg, & Jansson, 2002). Shift workers also experience a 40% increased risk for CVD, coronary artery disease, and HTN, an increased risk that may be related to shift work-associated sleep disturbances (Wolk et al., 2005). Shift work significantly predicts disturbed sleep (OR: 1.56) (Akerstedt et al., 2002), and working night shifts increases sleepiness and sleepiness-related risk for driving accidents, long blinks while driving, and variability in driving patterns (Akerstedt, Kecklund, & Gillberg, 2007). Overall, sleep disturbances affect CVD risk and shift workers experience concomitant increases in sleep disturbances and CVD risk.

The physiological mechanisms underlying the relationship sleep and disease risk require further elucidation; however, potential mechanisms may include increased sympathetic nervous system activity, decreased anti-oxidant enzyme activity, or impaired endothelium-dependent vasodilation due to chronic sleep deprivation (Wolk et al., 2005). The physiological effects of acute sleep deprivation appear to differ from chronic sleep deprivation, with acute deprivation corresponding with increased blood pressure and decreased muscle sympathetic nerve activity (Wolk et al., 2005). Acute and chronic sleep deprivation correlate with greater activation of inflammatory processes, such as elevated C-reactive protein levels, increased leukocytes, and elevated inflammatory cytokines (IL-6 and TNF-α) (Wolk et al., 2005). Finally, sleep deprivation may independently correlate with negative metabolic changes, such as glucose intolerance, insulin resistance, and a blunted insulin response to glucose (Wolk et al., 2005). Similarly, potential mechanisms underlying the relationship between shift work-related sleep disturbances and CVD include increased cardiac sympathetic and decreased cardiac parasympathetic activity, which may negatively affect circadian blood pressure control and decrease endothelial function (Wolk et al., 2005). Shift work-related increases in CVD risk may also correlate with increased obesity, dyslipidemia, and changes in lipid and glucose tolerance (Wolk et al., 2005). Each of these mechanisms provide a plausible explanation underlying the effects of sleep-disturbances on disease risk; however, additional research is required to further understand these mechanisms, particularly the metabolic effects of sleep disturbances.

Along with considering the direct physiological link between sleep disturbances and chronic disease risk, sleep may indirectly affect chronic disease risk via its relationship with weight status. Indeed, obese individuals exhibit an inverse relationship between weight and sleep time, an association that may be related to changes in cortisol levels, growth hormone secretion, leptin levels, or other factors associated with metabolic dysregulation (Wolk et al., 2005). Obesity represents a primary risk factor for obstructive sleep apnea, which is significant because sleep apnea changes hemodynamic and neuroendocrine effects and decreases oxygen saturation (Wolk et al., 2005). A 10% weight gain also corresponds with a six-fold increased odds for developing sleep apnea, and weight loss decreases the severity of sleep apnea (Wolk et al., 2005). The effects of weight status on sleep apnea cause concern because of the negative acute effects of sleep apnea on health, including hypoxemia and hypercapnia leading to increased vascular sympathetic nerve activity, vasoconstriction, and arterial blood pressure (Wolk et al., 2005). Sleep apnea also triggers ischemia with ST-segment depression, increased platelet activation, elevated fibrinogen levels, and other changes associated with a prothrombotic state, all of which may explain the positive correlation between sleep apnea, stroke, CHF, and CVD mortality (Wolk et al., 2005). Sleep apnea triggers bradyarrhythmias, such as AV block and sinus arrest, as well as supraventricular and ventricular tachyarrhythmias (Wolk et al., 2005). These acute effects of sleep apnea may explain the correlation between the severity of sleep apnea and the risk of nocturnal sudden cardiac death (Wolk et al., 2005). Chronic sleep apnea increases the risk for HTN via enhanced sympathetic activity, elevated catecholamine levels, etc., and it may promote atherosclerosis due to increased oxidative stress, sympathetic activation, endothelial dysfunction, and greater inflammation (Wolk et al., 2005). Clearly, sleep apnea negatively affects cardiovascular risk factors and associated outcomes, and obesity likely increases risk for sleep apnea. However, there may also exist a reciprocal relationship between sleep apnea and weight status, with research suggesting that chronic sleep apnea increases obesity risk due to increased VAT, leptin resistance, and obesity-induced metabolic abnormalities, such as insulin resistance, glucose intolerance, overt DM, and metabolic syndrome (Wolk et al., 2005). This

reciprocal relationship between obesity and sleep apnea causes particular concern, as it suggests that obesity and sleep apnea may synergistically increase CVD risk.

Overall, research suggests that sleep likely represents an important health behavior to consider when attempting to modify disease risk. Additionally, the relationship between sleep apnea and weight status suggests that researchers should likely consider the individual and combined effects of sleep and weight status when attempting to unravel the relationship between said variables and disease risk. PA may also interact with sleep, as research indicates that PA improves sleep quality (Harma, Tenkanen, Sjoblom, Alikoski, & Heinsalmi, 1998), suggesting that the effects of PA on health outcomes may be partially due to PA effects on sleep. As, such, researchers should consider the roles of weight status and PA when examining the relationship between sleep and health outcomes.

Researchers with data scientists' statistical skills and substantive expertise in health can help inform the design and analysis of studies attempting to unravel the complex relationships among the health behaviors discussed throughout this section, including weight status, physical activity/inactivity, SB, and sleep with health outcomes. Research to-date suggests that each of these health behaviors uniquely contributes to health outcomes and that many of these behaviors interact with one another by moderating or mediating effects on health outcomes. A thorough examination of the effects of each of these health behaviors requires consideration of the specific methods used for assessing said behaviors, because the methods used affects the interpretation of outcomes. Incorporating substantive expertise into the entire process, from study design through the interpretation of outcomes, will help guide the use of appropriate methods, statistical analyses, and interpretation of outcomes. Appropriate statistical analyses can help researchers identify meaningful cut-points for a given health behavior for affecting health outcomes, for example, determining the dose of PA required to reduce CVD risk. Identifying meaningful cut-points or 'doses' of health behaviors could help inform clinicians regarding what information to communicate with their patients and could help individuals make informed decisions regarding how they can change their health behaviors to improve their health outcomes and enhance their quality of life.

Psychosocial Determinants of Health and Health Behaviors

Understanding the health behaviors that predict chronic disease risk and associated health outcomes represents an important first step to improving health outcomes. However, simply knowing which health behaviors matter is insufficient, and to successfully improve health outcomes via changes in health behaviors, researchers must also understand which variables predict health behaviors. A wide range of variables affect health behaviors, and health behavior change theories and models typically attempt to address these variables. Common variables of interest in behavior change models include self-efficacy, knowledge, intentions, outcome expectations, motivation, skills, planning, etc. (Sniehotta, Scholz, & Schwarzer, 2005). Many of these variables fall under the category of psychosocial determinants of health, and interventions typically identify one or more psychosocial determinants to target to successfully promote positive changes in health behaviors, with the long-term goal of reducing chronic disease risk and improving health outcomes. While a variety of psychosocial determinants affect health behaviors, this section will focus on three potential psychosocial determinants of health behaviors: 1) Psychological stress; 2) Motivation; and 3) Action Planning. However, these psychosocial determinants represent only a small proportion of the potential determinants of health behaviors.

Stress

Psychosocial stress is one psychosocial determinant of health behaviors that directly affects chronic disease risk and health outcomes. Psychosocial stress is defined as the "perception that the demands (or anticipated demands) of the environment exceed the individual's ability to cope" (Neu, Matthews, King, Cook, & Laudenslager, 2014). Psychosocial stress directly affects chronic disease risk, with chronic exposure to daily stressors predicting CVD morbidity and mortality, independent of CVD severity (Babyak et al., 2010; Cohen, Edmondson, & Kronish, 2015; Sheps et al., 2002; Steptoe & Kivimaki, 2013). Chronic psychosocial stress, both in early life and adulthood, corresponds with a 40%-60% increased risk of CHD (Steptoe & Kivimaki, 2013). Specific psychosocial stressors linked to increased CVD risk include social isolation, stress at work, marital problems, death of a child, and having to care for a sick spouse (Steptoe & Kivimaki, 2013). Importantly, some data have helped rule out the

possibility of reverse causality, in which individuals with underlying subclinical CVD might be more likely to report stress, as studies excluding CVD events in the first five years after baseline found that the association between job strain and clinical CVD remained the same (Kivimaki et al., 2012; Steptoe & Kivimaki, 2013).

Psychosocial stressors also predict increased risk of CVD events, with both social isolation and loneliness corresponding with a 50% increased RR of incident CVD events (Cohen et al., 2015). Work-related stress increases RR for incident CVD events by 40% (Cohen et al., 2015), and working long hours corresponds with a 40% increased risk of incident CVD (Steptoe & Kivimaki, 2013; Virtanen et al., 2012). Emotional stress may account for a small percent of the PAF for acute cardiac events (Nawrot, Perez, Kunzli, Munters, & Nemery, 2011; Steptoe & Kivimaki, 2013). Anger, stress, and other emotions correlate with episodes of MI (Babyak et al., 2010; Sheps et al., 2002; Steptoe & Kivimaki, 2013), and the odds of experiencing a negative emotion during the two hours prior to stroke onset is extremely high (OR: 14.0) (Koton, Tanne, Bornstein, & Green, 2004). Chronic exposure to psychosocial stressors predicts a worse prognosis in CVD patients (Cohen et al., 2015; Steptoe & Kivimaki, 2013). For example, work-related stress predicts recurrent cardiac events after an MI and, among MI survivors, mortality over 2-years of follow-up occurred among 13% of patients reporting moderate or high stress, versus 9% among patients with low stress (Arnold, Smolderen, Buchanan, Li, & Spertus, 2012; Steptoe & Kivimaki, 2013). Clearly, psychosocial stressors negatively affect the risk for CVD, CVD-related events, and prognosis in individuals with CVD.

Stress-related cardiomyopathy provides the most striking example of the importance of psychosocial stress in affecting health outcomes. Stress-related cardiomyopathy is characterized by chest pain and shortness of breath, moderately elevated cardiac enzymes, EKG abnormalities, like ST elevation, and a weakening of the cardiac muscles, and it accounts for 2% of suspected acute coronary syndromes (Steptoe & Kivimaki, 2013). Interestingly, stress-related cardiomyopathy is temporary and reversible, and often occurs in people with little to no structural coronary artery disease, thus distinguishing it from the majority of cardiomyopathies (Steptoe & Kivimaki, 2013). Intense episodes of acute physical or

emotional stress precede the onset of stress-related cardiomyopathy in 42% and 47% of cases, respectively (Sharkey et al., 2010; Steptoe & Kivimaki, 2013). Elevated catecholamine levels may explain the onset of stress-related cardiomyopathy, as the features of stress-related cardiomyopathy also occur with intravenous catecholamines or beta-receptor agonists (Steptoe & Kivimaki, 2013; Wittstein et al., 2005). However, additional research is required to fully understand the physiological mechanisms underlying stress-related cardiomyopathy.

Chronic stress exposure also increases the risk for metabolic syndrome, with studies operationalizing chronic stress exposure as low SES finding that low SES predicts increased risk for metabolic syndrome (Brunner et al., 1997; Loucks et al., 2007; Manuck, Phillips, Gianaros, Flory, & Muldoon, 2010; Park et al., 2012; Ramsay, Whincup, Morris, Lennon, & Wannamethee, 2008; Steptoe & Kivimaki, 2013). Other psychosocial stressors, including loneliness, marital stress (in women), and workplace stress longitudinally predict incident metabolic syndrome, even after controlling for SES (Steptoe & Kivimaki, 2013). The British Whitehall II study revealed that individuals reporting a greater frequency of stress over time experienced a greater risk of metabolic syndrome, which explained 16% of the effect of stress on CHD (Chandola et al., 2008). Chronic stress correlates with higher triglycerides and lower HDL-cholesterol (Chandola et al., 2008; Kivimaki et al., 2009; Steptoe & Kivimaki, 2013); however, changes in LDL- and HDL-cholesterol and triglycerides explain very little of the association between stress and CVD (Chandola et al., 2008; Kivimaki et al., 2002; Steptoe & Kivimaki, 2013). Stress transiently increases blood pressure, and there is a dose-response pattern in the association between stress associated with loneliness and increased blood pressure (Hawkley, Masi, Berry, & Cacioppo, 2006; Shankar, McMunn, Banks, & Steptoe, 2011), a response that strengthens with increasing age (Hawkley et al., 2006; Steptoe & Kivimaki, 2013). However, these transient, stress-induced increases in blood pressure may not correspond with chronic HTN, indeed, the Whitehall II study showed little support for HTN mediating the relationship between stress and CVD (Kivimaki et al., 2002; Steptoe & Kivimaki, 2013). Stress may increase abdominal fat deposition, and chronic stress correlates with higher central obesity and BMI (Chandola et al., 2008; Kivimaki et al., 2009; Steptoe & Kivimaki, 2013). Finally,

higher stress correlates with immune system dysfunction, a multitude of cognitive impairments, depression, and burnout (Mucke, Ludyga, Colledge, & Gerber, 2018). Overall, it is clear that stress correlates with metabolic syndrome risk and CVD risk factors, though the role of these risk factors in mediating the relationship between stress exposure and CVD risk require further elucidation.

The physiological mechanisms underlying the effects of psychosocial stress on CVD risk and other health outcomes remain undetermined. However, changes in blood flow, coronary artery calcium, and acute myocardial ischemia triggered by stress may represent potential mechanisms underlying said relationship. Among individuals with post-traumatic stress disorder (PTSD), common physiological changes include decreased myocardial blood flow, increased coronary artery calcium, and evidence of myocardial ischemia on a treadmill test (Cohen et al., 2015). Psychological stressors also induce acute myocardial ischemia in 30-70% of patients with existing coronary artery disease (Cohen et al., 2015; Krantz & Burg, 2014). Oddly, stress-induced myocardial ischemia typically fails to cause ischemic symptoms, like chest pain; however, stress-induced myocardial ischemia does correspond with increased mortality risk and risk of recurrent CVD (Cohen et al., 2015). As such, it is possible that distinct mechanisms underlie the differences between the symptoms of stress-induced myocardial ischemia and other forms of myocardial ischemia (Cohen et al., 2015; Jiang et al., 2013; Strike & Steptoe, 2003).

For example, coronary microvascular dysfunction occurs with stress-induced myocardial ischemia, and leads to atypical symptoms like fatigue and vague discomfort (Cohen et al., 2015; Jiang et al., 2013; Strike & Steptoe, 2003). Acute exposure to experimental stressors triggers heightened platelet activation among patients who survived a stress-induced acute MI, but does not occur among patients who survived a non-stress-induced MI, suggestion that coagulation may play an important mechanistic role in the relationship between stress and CVD (Steptoe & Kivimaki, 2013; Strike et al., 2006). Stress may also trigger the accumulation of atherosclerotic plaques which, in combination with heightened platelet activation, may increase the risk for CVD events (Cohen et al., 2015). Importantly, adjusting for other CVD risk factors, like smoking, HTN, DM, dyslipidemia, and obesity barely attenuates the relationship between stress, myocardial ischemia, and coronary atherosclerosis (Cohen et al., 2015). As

such, stress may trigger different mechanisms underlying the development of myocardial ischemia and atherosclerosis; however, substantially more research is needed to elucidate these mechanisms.

Increased hypothalamic-pituitary-adrenal (HPA) axis activity, autonomic nervous system reactivity, inflammation, endothelial dysfunction, and oxidative stress may also underlie stress effects on CVD (Cohen et al., 2015; Steptoe & Kivimaki, 2013). Exposure to acute psychological stressors, chronic daily stressors, traumatic events, and PTSD correlates with these changes; however, research has not examined whether these changes account for the association between psychosocial stress and CVD (Cohen et al., 2015; Kivimaki et al., 2012; Kivimaki et al., 2006; Kloner, McDonald, Leeka, & Poole, 2009; Koton et al., 2004; Lampert et al., 2002; Lampert et al., 2009; Shahidi, Sannes, Laudenslager, & Maluf, 2015). The HPA axis plays an important role in regulating the body's response to physical and mental stress (Neu et al., 2014). HPA axis activation triggers cortisol production, which mobilizes energy reserves, increases cerebral perfusion and glucose utilization, reduces inflammation, and enhances cardiovascular function, all to achieve the goal of helping an individual cope with stressors (Neu et al., 2014). Short-term or mild stress triggers transient increases in cortisol levels that return to normal when the stressor disappears (Neu et al., 2014). However, with prolonged stress, cortisol levels remain high, and this chronic stimulation of glucocorticoid receptor synthesis inhibits adrenocorticotropic hormone (the hormone that promotes cortisol release), resulting in lower cortisol production and a state of hypo-cortisolism (Neu et al., 2014; Schommer, Hellhammer, & Kirschbaum, 2003; Shahidi et al., 2015). Importantly, cortisol responsivity to acute stress may predict the progression of coronary artery calcification, independent of other risk factors (Hamer, Endrighi, Venuraju, Lahiri, & Steptoe, 2012; Hamer & Steptoe, 2012; Steptoe & Kivimaki, 2013). Thus, research supports the role of stress in affecting chronic HPA axis activation, which causes changes in glucose utilization, inflammation, and cardiovascular function, thereby explaining one physiological mechanism potentially underlying the effects of stress on CVD.

Stress can also transiently impair endothelial function, increase circulating levels of pro-inflammatory cytokines (i.e. IL-6, TNF-alpha), increase platelet activation, and promote prothrombotic

changes in the blood, physiological mechanisms that may also account for the effects of stress on CVD (Hjemdahl & Von Kanel, 2012; Steptoe & Kivimaki, 2013). There are significant within-person differences in the magnitude of physiological responses to stress and the post-stress recovery period (Steptoe & Kivimaki, 2013), differences that may relate to coping techniques (Cohen et al., 2015). For example, animal research suggests that coping responses moderate the relationship between the neurobiological pathways associated with stress and cardiovascular damage (Cohen et al., 2015). Rodents who use passive, rather than active, coping strategies exhibit greater HPA axis reactivity and activation of proinflammatory genes, along with increased cardiac hypertrophy and reduced heart rate variability (Cohen et al., 2015); however, significantly more research in humans is needed to help understand within-person differences in stress responses. When considering post-stress recovery, one study revealed a significant and positive longitudinal relationship between impaired post-stress recovery and changes in carotid artery intima-media thickness (r=0.14) (Chida & Steptoe, 2010; Steptoe & Kivimaki, 2013). Epidemiological data also indicate that greater life stress across time increases cardiovascular reactivity, which correlates with faster progression of carotid artery intima-media thickness, suggesting that cardiovascular reactivity may mediate the relationship between chronic stress and intima-media thickness (Low, Salomon, & Matthews, 2009; Steptoe & Kivimaki, 2013); however, these effects of stress on intima-media thickness may only occur in males (Hintsanen et al., 2005).

While stress directly affects disease risk due to underlying physiological mechanisms, stress also indirectly affects disease risk by affecting health behaviors. Stress inversely correlates with and predicts decreased PA participation across time (Bauman et al., 2012; Gerber & Puhse, 2009; Oaten & Cheng, 2005; Schultchen et al., 2019; Steptoe et al., 1997; Stetson, Rahn, Dubbert, Wilner, & Mercury, 1997; Stults-Kolehmainen & Sinha, 2014). Individuals who experience high stress levels also engage in less exhausting activities and avoid PA (Schultchen et al., 2019). However, while stress may decrease PA participation, PA participation may also decrease stress, with cross-sectional and longitudinal research indicating that greater PA participation corresponds with lower stress levels (Aldana, Sutton, Jacobson, & Quirk, 1996; Bennett et al., 2006; Gerber & Puhse, 2009; Kornitzer & Kittel, 1986; Kouvonen et al.,

2005; Melamed, Kushnir, Strauss, & Vigiser, 1997; Schnohr, Kristensen, Prescott, & Scharling, 2005; Wemme & Rosvall, 2005). This supports the idea that there exists a reciprocal relationship between stress and PA (Schultchen et al., 2019).

The reciprocal relationship between stress and PA occurs both between- and within-people, with ecological momentary assessment (EMA) data indicating that, within-persons, higher stress significantly correlated with lower PA over the next few hours, and greater PA correlated with better self-reported measures of subjective stress, less subsequent stress, lower negative affect, and higher positive affect (Schultchen et al., 2019). Additionally, higher negative affect correlated with lower PA (Schultchen et al., 2019). Indeed, when stressed, individuals typically exhibit unhealthy behaviors, liking being physically inactive (Schultchen et al., 2019), which is particularly unfortunate given the potential value PA may provide for dealing with stress. Perhaps most importantly, this study found that regular PA correlated with decreases in physiological indicators of stress, including lower salivary cortisol, lower heart rate, and faster cardiovascular recovery after stress exposure (Schultchen et al., 2019). These EMA findings are particularly noteworthy, because they demonstrate that the reciprocal relationship between stress and PA exists within individuals, suggesting that person-specific characteristics do not drive the directionality of the stress-PA relationship.

The physiological mechanism underlying the attenuating effects of PA on individuals' stress reactivity could be due to a training effect. The cross-stressor-adaptation (CSA) hypothesis suggests that regular exposure to physical stress, like moderate or vigorous PA, trains the body to more effectively handle all stressors, including psychosocial stressors (Kjaer, 1992; Luger et al., 1987; Mucke et al., 2018). The CSA hypothesis suggests that physical stress triggers a similar stress response to that of psychosocial stressors (Kjaer, 1992; Luger et al., 1987; Mucke et al., 2018), thereby promoting beneficial adaptations of the HPA axis and the sympathoadrenal medullary system, which can generalize to non-physical stressors (e.g. psychosocial stressors) (Gerber, 2017; Mucke et al., 2018). These beneficial adaptations could therefore account for regular PA attenuating the effects of stress on health outcomes (Gerber, 2017; Mucke et al., 2018). Changes in neurotransmitter levels may also underlie the relationship between PA

and stress. PA increases dopamine, serotonin, and endorphin release, all of which increase positive affect and decrease negative affect (Meeusen & De Meirleir, 1995; Ruscheweyh et al., 2011; Schultchen et al., 2019; Sutoo & Akiyama, 2003; Winter et al., 2007). PA also increases self-efficacy, which can subsequently enhance momentary affect (Pannicke, Reichenberger, Schultchen, Pollatos, & Blechert; Rhodes & Kates, 2015; Schultchen et al., 2019). Overall, PA directly affects psychological stress and stress reactivity, thereby potentially moderating or mediating the relationship between stress and health outcomes.

Stress also affects sleep, with cross-sectional research indicating that higher stress correlates with shorter sleep duration and impaired sleep (Benham, 2010; Petersen, Kecklund, D'Onofrio, Nilsson, & Akerstedt, 2013). Moderate everyday stress correlates with decreased time spent in deep sleep, increased time in lighter sleep, anxiety at bedtime, and poor sleep quality (Akerstedt et al., 2007). Individuals reporting higher perceived stress also demonstrate shorter sleep times, worse sleep quality, higher likelihood of sleep apnea, and greater sleepiness and fatigue (Kashani et al., 2012). Finally, stress correlates with insomnia, likely because stress makes it difficult to fall asleep, to stay asleep, and affects overall sleep quality (National Sleep Foundation, 2019), and stress represents one of the primary causes of persistent psychophysiological insomnia (Akerstedt et al., 2012; Petersen et al., 2013).

Prospective research indicates that high work demands, work-related stress, and prior stressful life events predict insomnia, greater sleep disturbance, worse sleep quality, impaired sleep, and greater sleep variability (Akerstedt et al., 2012; de Lange et al., 2009; Ribet & Derriennic, 1999). Moderate daily stress predicts worse sleep, decreased sleep efficiency, and worse sleep fragmentation, and decreased sleep quality (Akerstedt et al., 2012; Petersen et al., 2013). This prospective research also suggests that there is a reciprocal relationship between stress and sleep quality, with greater stress predicting worse sleep quality, and worse sleep quality predicting increased stress at bedtime the following night (Akerstedt et al., 2012). Indeed, Akerstedt et al. concluded that, since significant variability in stress and sleep quality occur within a modest range, sleep quality is likely very sensitive to small changes in stress (Akerstedt et al., 2012). Additionally, sleepiness and stress predict day-to-day variation in fatigue, and

said fatigue corresponds with greater sleepiness on the same day (Akerstedt, Axelsson, Lekander, Orsini, & Kecklund, 2014). Cross-sectional and longitudinal research confirm the relationship between stress and multiple sleep metrics (i.e. sleep duration, sleep quality, etc.), as well as the likely presence of a reciprocal relationship between stress and sleep.

The physiological mechanisms underlying the effects of stress on sleep likely relate to effects on HPA axis activation, with data suggesting that the HPA axis and sleep exhibit a reciprocal relationship, and increased secretion of corticotrophin-releasing hormone predicts lighter sleep, more sleep awakenings, and less time spent in deep sleep (Dahlgren, Kecklund, Theorell, & Akerstedt, 2009). High cortisol levels inhibit deep sleep, whereas low cortisol levels may enhance deep sleep (Dahlgren et al., 2009), which may account for the negative effects of stress on sleep, since acute stress increases cortisol. Deep sleep inhibits HPA axis activity (Dahlgren et al., 2009), which implies a reciprocal relationship between stress and sleep. Similarly, sleep disruptions alter nighttime cortisol secretions, and elevated cortisol in the evening time occurs after partial sleep deprivation and in insomniacs (Dahlgren et al., 2009). Experiencing greater stress, anxiety, and fatigue corresponds with elevated evening cortisol levels and higher anxiety corresponds with lower cortisol levels the following morning, subsequently predicting higher levels of sleepiness (Dahlgren et al., 2009). Finally, high exhaustion and anxiety correspond with low cortisol on the following morning (Dahlgren et al., 2009). These data provide support for the reciprocal relationship between stress and sleep, with HPA axis activation as the physiological mechanism underlying this reciprocal relationship. Considering the physiological effects of HPA axis activation on health outcomes, the combination of higher stress and worse sleep may exacerbate the independent effects of stress and sleep on health outcomes. Indeed, Benham argues that models examining the effects of stress on health outcomes should include sleep, and that such models should conceptualize stress and sleep as reciprocally affecting one another, with both variables indirectly affecting health outcomes by increasing allostatic load (i.e. HPA axis activation) (Benham, 2010).

Stress clearly represents an important direct and indirect psychosocial determinant of health outcomes. The direct effects of stress on health outcomes likely occur via effects on HPA axis activation,

inflammation, endothelial functioning, etc., and the indirect effects occur via effects on weight status, PA, and sleep. Stress exhibits reciprocal relationships with multiple health variables, including weight status, PA, and sleep, suggesting that researchers attempting to understand the precise role of stress in affecting health outcomes need to account for these reciprocal relationships. Researchers trained in employing statistical models capable of accounting for such reciprocal relationships can enhance our understanding of how unique variables, such as stress, directly and indirectly affect health outcomes.

Motivation

Motivation is another psychosocial determinant of PA. Well-established behavior change theories help provide guidance when researchers are attempting to understand the potential effects of motivation on health behaviors. Self-Determination Theory (SDT) represents one of the most well-established behavior change theories regarding how motivation affects health behaviors (Ryan & Deci, 2000). SDT states that motivation drives people to engage in a behavior, and suggests that some forms of motivation completely align with an individual's values, whereas, other forms of motivation may be completely external to a person (Ryan & Deci, 2000). SDT conceptualizes these various types of motivation on a continuum from non-autonomous amotivation to completely autonomous intrinsic motivation, with four subcategories of extrinsic motivation in between (Ryan & Deci, 2000). Amotivation refers to a state in which a person has no drive for a behavior and experiences a complete lack of autonomy regarding said behavior (Ryan & Deci, 2000). This can occur due to a lack of perceived competence, due to the fact that a person believes the given behavior is not valuable, or because they are motivated not to do an action, for instance, as a form of defiance (Ryan & Deci, 2000). For example, a child may experience amotivation regarding participating in an organized sport, like baseball, if their parents force them to do it or if they feel incompetent in their ability to play baseball. Individuals may experience a lack of perceived competence for specific types of PA, or they may feel they aren't fit enough to be active (Korkiakangas, Alahuhta, & Laitinen, 2009; Teixeira, Carraca, Markland, Silva, & Ryan, 2012). Individuals may also simply not value PA, a common occurrence, as 40% of Europeans agreed with the statement that "Being physically active does not really interest me – I would rather do other things with my spare time"

(Teixeira et al., 2012). Importantly, amotivation may increase the likelihood that an individual does not participate in PA (Ryan & Deci, 2000).

The four subcategories of extrinsic motivation vary in the extent to which they are autonomously regulated (Ryan & Deci, 2000; Teixeira et al., 2012). External and introjected regulation are the least autonomous forms of extrinsic motivation (Ryan & Deci, 2000; Teixeira et al., 2012). These forms of motivation suggest that the individual does not have much control over their source of motivation, and they are often combined to represent controlled motivation (Ryan & Deci, 2000; Teixeira et al., 2012; Williams, Grow, Freedman, Ryan, & Deci, 1996). Controlled forms of extrinsic motivation occur when an individual participates in a behavior due to their desire to be compliant, to conform, or to avoid punishment or receive rewards (Ryan & Deci, 2000). For example, a person may participate in PA to be compliant with their doctor's direction to be active to reduce their LDL-cholesterol or lose weight, or they may also participate in PA as a means to an end, such as to look better (Markland, 2009; Teixeira et al., 2012). Greater controlled motivation corresponds with lower PA participation, because it does not reflect an individual's internal values (Ryan & Deci, 2000; Teixeira et al., 2012), or it has no effect on PA participation (Teixeira et al., 2012).

Identified and integrated regulation represent more autonomous forms of extrinsic motivation (Ryan & Deci, 2000; Teixeira et al., 2012). These two forms of extrinsic motivation suggest that the individual has more control over their source of motivation (Ryan & Deci, 2000). For example, a person may participate in PA because it is important to them, or it fits with their self-perception (Markland, 2009; Teixeira et al., 2012). Similar to identified and integrated regulation, intrinsic motivation represents the most autonomous form of motivation (Ryan & Deci, 2000; Teixeira et al., 2012). Intrinsic motivation occurs when a behavior aligns with an individual's interests, enjoyment, and sense of satisfaction (Ryan & Deci, 2000). For example, an individual might participate in PA because it makes them feel good or they enjoy the particular activity, such as playing volleyball with friends. Researchers often combine identified regulation, integration regulation, and intrinsic motivation to represent autonomous motivation (Ryan & Deci, 2000; Teixeira et al., 2012). SDT and related research examining the effects of motivation

on PA participation consistently indicate that more autonomous forms of motivation correlate with more persistent engagement in MVPA (Ryan & Deci, 2000; Teixeira et al., 2012).

Teixeira et al. conducted a review of the relationship between motivation and PA, finding consistent support that greater autonomy corresponded with greater PA participation (Teixeira et al., 2012). They also found that controlled motivation for PA only predicted short-term adoption of PA (Teixeira et al., 2012). In contrast, autonomous motivation predicted long-term PA participation in a wide range of participants and settings (Teixeira et al., 2012). Specific sources of autonomous motivation that predicted greater PA participation included social engagement, overcoming challenges associated with PA, and the desire to develop PA skills (Teixeira et al., 2012). Overall, the review supported the idea that valuing the outcomes of PA, like changes in physique, is an important source of motivation predicting PA adoption; whereas, valuing the experience of PA, like the social engagement, is an important source of motivation predicting longer-term PA participation (Teixeira et al., 2012). Barbeau et al. conducted a path-analysis that reinforced the value of autonomous motivation in predicting PA, revealing that characteristics of autonomous motivation that meet the psychological needs of competence and relatedness significantly and positively predicted autonomous motivation, subsequently predicting PA participation (Barbeau, Sweet, & Fortier, 2009). Importantly, the positive effects of autonomous motivation on PA participation occur throughout the lifespan, with research indicating that children who maintained higher autonomous motivation, and who valued the experience of PA, showed smaller declines in PA between middle-school and high-school (Dishman, McIver, Dowda, & Pate, 2018). Children with higher autonomous motivation for PA also demonstrated larger declines in valuing PA as a means to an end, such as for improving appearance, which is a form of controlled motivation (Dishman et al., 2018), suggesting that autonomous motivation related to PA enjoyment may help displace more controlled forms of motivation. However, researchers also found that children who maintained higher autonomous motivation demonstrated larger declines in valuing PA for social or competence reasons (Dishman et al., 2018); therefore, the effects of children's values on their levels of autonomous and controlled motivation for PA, as well as their subsequent PA participation, may be more complex than

previously thought. As such, research examining how children's values affect their type of motivation regarding PA, and how this affects PA participation, requires additional consideration.

Overall, research consistently indicates that autonomous motivation positively predicts PA participation (Barbeau et al., 2009; Dishman et al., 2018; Teixeira et al., 2012), and that psychological needs fulfillment, like experiencing competence and relatedness, fosters autonomous motivation (Barbeau et al., 2009; Teixeira et al., 2012). Therefore, motivation represents an important psychosocial variable predicting PA participation; however, the precise relationship between psychological needs fulfillment, values, and motivation in children requires further examination. Researchers attempting to influence PA participation to promote better health outcomes should consider attempting to increase individual's autonomous motivation for PA and reducing amotivation or controlled motivation for PA. Researchers attempting to disentangle the influence of different types of motivation on PA participation should consider using data scientists' statistical skills to examine the relationships between different types of motivation in predicting PA participation.

Action Planning

While motivation clearly represents an important predictor of PA participation, simply focusing on motivation may be insufficient, as substantial research indicates that, despite being motivated, individuals often fail to participate in PA (Sniehotta et al., 2005). This incongruence between motivation for participating in PA and actual PA participation may relate to an individual's intentions or their ability to use action planning (K. Li, Iannotti, Haynie, Perlus, & Simons-Morton, 2014; Sheeran, 2002; Sniehotta et al., 2005). Intentions are the explicit decisions an individual makes to act in a particular way, and they relate to motivation by helping to focus a person's motivation towards a goal (Sheeran, 2002). Therefore, intentions may help move motivation towards action. Many behavior change theories explicitly acknowledge the importance of behavioral intentions in predicting health behaviors, like PA (Ajzen, 1991; Fishbein & Ajzen, 1980; Maddux, 1993; Sniehotta et al., 2005). Indeed, previous research indicates that PA intentions explain a significant amount of variance in exercise participation 6-10 weeks post cardiac rehabilitation treatment (Blanchard, Courneya, Rodgers, Daub, & Knapik, 2002; Sniehotta et al.,

2005). Intentions also predict motivation related variables, with self-efficacy (*b*=0.63), outcome expectancies (*b*=0.25), and risk awareness (*b*=0.11) accounting for 65% of variance in intention, and intention significantly predicting PA participation (Sniehotta et al., 2005). Despite the importance of intentions in predicting and promoting behaviors, research reveals a gap between an individual's behavioral intentions and their actual behaviors, which is typically referred to as the "intention-behavior gap" (Sniehotta et al., 2005). This consistent presence of the intention-behavior gap resulted in researchers postulating which variables might help explain the gap, with the goal of identifying intervention targets to close the intention-behavior gap. Action planning was identified as one potential variable affecting intentions and the intention-behavior gap.

Action planning refers to when someone makes the conscious decision to engage in a behavior, often by literally putting the behavior on their schedule (i.e. scheduling an hour long run), and can include things such as making concrete plans that account for a variety of situations, including when to be active, where to be active, and what to do for activity (K. Li et al., 2014; Sniehotta et al., 2005). For example, an individual may plan on taking an hour long run in their neighborhood at 8AM. They may also have a contingency plan to go running at the gym if it's raining outside. Sniehotta et al. found that action planning significantly mediated the relationship between intentions and PA participation, with intentions predicting action planning (*b*=0.41) and action planning predicting exercise behavior (*b*=0.25) (Sniehotta et al., 2005). Importantly, intentions did not significantly predict PA after including action planning in model, indicating that action planning accounted for the effects of intention on PA participation (Sniehotta et al., 2005). The combination of action planning and intentions also accounted for a substantial amount of variance in PA behaviors (R^2 = 0.24) (Sniehotta et al., 2005). Action planning mediates the relationship between behavioral intentions and actual PA behavior in multiple settings (Cao, Schuz, Xie, & Lippke, 2013; K. Li et al., 2014; Reuter, Ziegelmann, Wiedemann, & Lippke, 2008; Scholz, Schuz, Ziegelmann, Lippke, & Schwarzer, 2008; Wiedemann, Lippke, Reuter, Ziegelmann, & Schwarzer, 2011), and interventions have successfully improved action planning as a means to increase PA participation (Dombrowski & Luszczynska, 2009; Koring et al., 2012). These findings suggest that

action planning helps explain the intention-behavior gap, and that interventions can successfully improve action planning to help close this gap. As such, researchers attempting to improve PA participation as a means to improve health outcomes should likely include action planning as a variable in their studies, as it represents an important link between motivation, intention, and behavior. The ability to account for these multiple predictors that interact with one another likely requires the inclusion of data scientists, whose skills allow them to simultaneously account for multiple psychosocial determinants of behaviors and to consider how said determinants interact with one another in predicting behavioral outcomes.

A wide variety of psychosocial variables predict health behaviors and, as described above, stress, motivation, and action planning represent important variables predicting PA participation. Understanding the roles of these psychosocial variables in predicting PA participation can help inform the development of more effective and targeted interventions. Such interventions have a greater likelihood of success. Data scientists are well-suited to helping researchers identify the unique and combined effects of psychosocial variables on health behaviors and associated health outcomes. This is particularly important when considering variables like stress, which indirectly affects health outcomes through effects on health behaviors, like PA, and directly affects health outcomes via physiological mechanisms, like HPA axis activation. Appropriate statistical modeling techniques can help disentangle the direct and indirect effects of stress on health outcomes, and can concomitantly examine the effects of different types of motivation (i.e. autonomous and controlled motivation) on health behaviors, as well as the role of action planning in mediating the relationship between motivation, intentions, and health behaviors. These represent only a few of the psychosocial determinants affecting health behaviors; however, they provide examples of the complex patterns between psychosocial variables, health behaviors, and health outcomes that may be understandable by employing appropriate methodological and statistical approaches.

Unmodifiable Determinants of Health

Along with the many psychosocial and behavioral determinants of disease, several unmodifiable variables also affect chronic disease risk. Such variables include age, sex, race/ethnicity, socioeconomic status, and genetics, among others. While these characteristics are unmodifiable by nature, researchers

should attempt to understand how they correspond with psychosocial determinants, health behaviors, and health outcomes. Identifying the potential effects of unmodifiable variables can allow researchers to design more appropriate studies and targeted interventions, and help inform public policy and health recommendations. Considering the wide variety of unmodifiable determinants of chronic disease risk and associated variables, this section will focus on three of the most commonly measured unmodifiable determinants examined in research studies: 1) Age; 2) Sex; and 3) Race/ethnicity.

Age

Age is unmodifiable because, while it does change across time, it progresses at the same rate between individuals and remains fixed at any given point in time. Age affects the prevalence of CVD, DM, and metabolic syndrome, and affects PA participation, SB, and the relationship between health behaviors and chronic disease risk. For example, an individual's likelihood of developing CVD increases with age and, in the U.S., 24-year-olds have a 20% risk of CVD, compared to 50% and 90% risks among 45-year-olds and 80-year-olds, respectively (American Heart Association, 2017). Age positively correlates with CVD risk, with the most significant increases for people over 60 years old (McAloon et al., 2016). The prevalence of exhibiting at least one CVD risk factor increases with age, with 65.0% of U.S. adults 60 years or older having HTN, compared to 76.5% of adults 80 years or older (Bromfield et al., 2014; Fryar, Chen, & Li, 2012; Mozaffarian et al., 2015; Nwankwo, Yoon, Burt, & Gu, 2013). Incidence rates for a first CVD event increase with age, with rates of 3 per 1000 among 35-44 year old males, versus 74 per 1000 among 85-94 year old males (Mozaffarian et al., 2015). Females exhibit similar incidence rates for a first CVD event approximately one decade later than males (45-54 years old and 35-44 years old, respectively); however, the age gap for these incident rates between males and females narrows with increasing age (Mozaffarian et al., 2015).

DM prevalence rates in the U.S. increase with age, with adults ≥ 20 years old versus ≥ 65 years old exhibiting prevalence rates of 9.9% and 26.9%, respectively (Cowie et al., 2009; Mozaffarian et al., 2015; Selvin et al., 2014). Global DM prevalence rates also increases with age, though income appears to moderate age-related increases in DM (Cho et al., 2018). For example, high-income countries exhibit the

highest DM prevalence rates among 75-79 year olds (22%); whereas, middle- and low-income countries exhibit the highest DM prevalence rates among 60-74 year olds (19%) and 55-64 year olds (8%), respectively (Cho et al., 2018). Metabolic syndrome prevalence rates increase with age (Mozaffarian et al., 2015), and age exacerbates the detrimental effects of DM and metabolic syndrome on CVD mortality risk (Church et al., 2009). CVD mortality rates among all males with DM are 5.5/1000 man years; whereas, rates among males ≥ 50 years old are 12.9/1000 man years (Church et al., 2009). Similar patterns for CVD mortality rates exist among males with metabolic syndrome, whose CVD mortality rates are 3.3/1000 man years among all males versus 8.0/1000 man years among males ≥ 50 years old (Church et al., 2009). Males ≥ 50 years old who have DM and metabolic syndrome also exhibit the highest CVD mortality rates compared to all males with DM and metabolic syndrome (14.8/1000 man years versus 6.5/1000 man years, respectively) (Church et al., 2009). Clearly, age affects the relationship between DM, metabolic syndrome and CVD mortality.

Given the age-related increase in the prevalence of CVD and other chronic diseases, it is unsurprising that obesity prevalence rates also increase. Among U.S. adults, 40-59 year olds exhibit significantly higher obesity prevalence rates than 20-39 year olds, with rates of 42.8% and 25.7%, respectively (Hales et al., 2017). However, adults 60 years and older do not exhibit significantly different obesity prevalence rates than other age groups (41.0%), a finding that may be due to age-related changes in muscle mass (Hales et al., 2017). Obesity prevalence rates similarly increase with age in children, with 6-11 year olds and 12-19 year olds exhibiting significantly higher obesity prevalence rates (18.4% and 20.6%, respectively) than 2-5 year olds (13.9%) (Hales et al., 2017). These age-related increases in obesity prevalence rates correspond with similar age-related increases in SB and decreases in PA.

A majority of studies indicate that PA participation decreases with age among children, adolescents, and adults (Bauman et al., 2012), and SB increases with age (Matthews et al., 2008). Among children, 6-11 year olds spend the least amount of time in SB (6.07 hours/day) compared to 12-15 year olds and 16-19 year olds (7.53 hours/day and 8.03 hours/day, respectively) (Matthews et al., 2008). Among adults, 20-29 year olds spend 7.48 hours/day in SB, and time spent in SB progressively increases

with age, with averages of 7.25 hours/day in 30-39 year olds, 7.55 hours/day in 40-49 year olds, 7.87 hours/day in 50-59 year olds, 8.41 hours/day in 60-69 year olds, and 9.28 hours/day in 70-85 year olds (Matthews 2008). The association between SB and cardiometabolic outcomes also varies by age; for example, the positive correlation between SB and triglycerides may be stronger in 18-59 year olds compared to adults ≥ 60 years old, possibly because older adults already have a poorer cardiometabolic profile and/or spend greater quantities of time in SB (Brocklebank et al., 2015). In contrast, the negative effects of total time spent in SB on WC, HDL-cholesterol, and C-reactive protein may worsen with age, and the negative effect of fewer breaks in SB on systolic blood pressure also increases with age (Healy et al., 2011). These data indicate that PA declines with age, SB increases with age, and age moderates the relationship between SB and cardiometabolic outcomes. The precise role of age in moderating the relationship between SB and cardiometabolic outcomes remains unclear, and additional research is needed.

Research consistently indicates that age correlates with the prevalence of chronic diseases, health behaviors like PA and SB, and the relationship between health behaviors and chronic disease. Therefore, researchers should consider examining age as a potential moderator of the relationship between health behaviors and health outcomes. Although it is impossible to change an individual's age, understanding the role age plays in affecting health outcomes can help inform clinicians and public health practitioners regarding what information to communicate to patients and the general public. Understanding the role of age could also help researchers and interventionists design stronger studies or more effective interventions. Clearly, age matters, and researchers and clinicians would do well to acknowledge the important role of age in affecting health behaviors and outcomes.

Sex

Biological sex is another unmodifiable variable that correlates the prevalence of chronic disease and health behaviors, and potentially moderates the effects of health behaviors on health outcomes. More males than females suffer from CVD, and males exhibit a higher CVD mortality burden as they age than do females (McAloon et al., 2016; Mozaffarian et al., 2015), with CVD-mortality rates of 275.7 per

100,000 and 192.3 per 100,000 in males and females, respectively (Mozaffarian et al., 2015). Though, females' CVD mortality burden accelerates post-menopause (McAloon et al., 2016). Males experience greater CVD risk, with 50 year old males and females having a 51.7% and 39.2% lifetime risk for developing CVD, respectively (Lloyd-Jones et al., 2010; Mozaffarian et al., 2015). The prevalence of CVD risk factors varies by sex, with U.S. males experiencing a higher likelihood of exhibiting at least one CVD risk factor than females (51.6% and 41.2%, respectively) (Fryar et al., 2012). The proportion of CVDs attributable to specific disease conditions vary by sex and age. For example, before 75 years of age, males demonstrate a larger proportion of CVD events that are attributable to CHD and females demonstrate a larger proportion that are attributable to stroke (Mozaffarian et al., 2015).

The prevalence of DM and metabolic syndrome vary by sex, with U.S. males demonstrating a slightly higher prevalence of DM compared to females (11.8% versus 10.8%, respectively), and, after adjusting for other risk factors, U.S. males experience a significantly greater risk for developing DM (Dabelea et al., 2007; Mozaffarian et al., 2015). Global DM prevalence rates reflect those in the U.S., with males demonstrating a slightly higher prevalence compared to females, at 8.9% and 8.4%, respectively (Cho et al., 2018). Globally, DM prevalence rates peak at different ages by sex, with males' prevalence rates peaking at 65-69 years of age and females' prevalence rates peaking at 70-79 years of age (Cho et al., 2018). The prevalence rates of metabolic syndrome are higher among males than females, and prevalence rates increase with age (Ervin, 2009; Mozaffarian et al., 2015). For example, prevalence rates among 20-39 year old males and females are 20.3% and 15.6%, respectively; whereas, prevalence rates among 40-59 year old males and females are 40.8% and 37.2%, respectively (Ervin, 2009; Mozaffarian et al., 2015). Finally, the effect of metabolic syndrome on CVD risk varies by sex, with RRs of 1.98 and 2.63 among males and females, respectively (Gami et al., 2007; Mozaffarian et al., 2015).

Contrary to CVD, DM, and metabolic syndrome, obesity prevalence rates do not vary by sex, and both sexes demonstrate consistent, linear increases in BMI and WC across time (Fryar et al., 2012). However, obesity prevalence rates do differ between males and females in specific racial/ethnic groups (Hales et al., 2017). Non-Hispanic Asian males demonstrate lower obesity prevalence rates than non-

Hispanic Asian females (10.1% and 14.8%, respectively), and non-Hispanic black males demonstrate lower obesity prevalence rates than non-Hispanic black females (36.9% and 54.8%, respectively) (Hales et al., 2017). Hispanic males demonstrate lower obesity prevalence rates than Hispanic females (43.1% and 50.6%, respectively) (Hales et al., 2017). As such, race/ethnicity appears to affect obesity prevalence rates in all of the racial/ethnic groups examined in NHANES with the exception of non-Hispanic whites (Hales et al., 2017). There are significant sex-differences in obesity-related mortality risk, with obese males experiencing a significantly higher risk of premature death than obese females, a finding that could be due to greater insulin resistance, hepatic lipid levels, and DM in obese males versus females (Dufour, 2018). Indeed, moderately obese males (BMI 30-35 kg/m^2) experience a 29.5% increased mortality risk, compared to a 14.6% increased risk among moderately obese females (Dufour, 2018). Similar to adults, obesity prevalence rates in children do not differ by sex (Hales et al., 2017). Contrary to adults, children do not exhibit significant sex differences in obesity prevalence rates within specific racial/ethnic groups (Hales et al., 2017). These data indicate a complex relationship between sex and obesity that may be moderated by other characteristics, such as age and race/ethnicity, suggesting that researchers may want to examine two or three way interactions between sex, age, and race/ethnicity to clarify how these unmodifiable characteristics relate to obesity prevalence.

With regard to PA participation, males participate in significantly more PA across all ages. Being male significantly predicts longitudinal PA participation among children aged 4-9 years old; however, being male only significantly correlates with, but does not predict, PA participation among adolescents and adults (Bauman et al., 2012). Male adults are more likely to meet PA recommendations than female adults (3.8% and 3.2%, respectively) (Mozaffarian et al., 2015; Troiano et al., 2008), and U.S. males engage in an average of 35 minutes of MVPA/day, whereas females engage in an average of 21 minutes of MVPA/day (Luke et al., 2011; Mozaffarian et al., 2015). This relationship between sex and PA also exists with regard to physical inactivity, and 28.6% of adult males report being physically inactive, compared to 32.3% of adult females (Mozaffarian et al., 2015). Adult females spend more time in SB than males; however, females also take more breaks from SB than males (Healy et al., 2011). Finally,

lifespan data indicate that females consistently spend more time in SB than males until middle adulthood (ages 50-59 years); however, among adults 60 years and older, males spend more time in SB than females (8.8 hours/day versus 8.0 hours/day, respectively) (Matthews et al., 2008).

Children exhibit similar sex differences in PA, physical inactivity, and SB, with data indicating that more male than female children meet PA recommendations (Mozaffarian et al., 2015; Troiano et al., 2008), and 11.2% of males versus 19.2% of females report having been physically inactive in the previous seven days (Kann et al., 2014; Mozaffarian et al., 2015). Females aged 6-11 years old spend more time in SB than males (6.1 hours/day and 6.0 hours/day in SB, respectively) (Matthews et al., 2008). Overall, data indicate that male adults and children typically participate in greater PA and demonstrate lower levels of physical inactivity and SB than females.

Importantly, sex may moderate the relationship between SB and health outcomes. For example, while females spend more time in SB than males, females still exhibit more favorable cardio-metabolic profiles, possibly due to the greater number of breaks females take from SB (Healy et al., 2011). Significant sex differences may also exist regarding the strength of the relationships between total sedentary time and breaks in SB with both sexes demonstrating significant relationships between total sedentary time and breaks in SB with blood pressure, triglycerides, and insulin (Healy et al., 2011). The one exception to this is HDL-cholesterol, for which only males demonstrate a significant association between total sedentary time and HDL-cholesterol; whereas, only females demonstrate a significant association between breaks in SB and HDL-cholesterol (Healy et al., 2011).

Similar to findings regarding age, sex clearly relates to health behaviors and chronic disease, affecting prevalence rates and the relationships between health behaviors and chronic disease. As such, researchers should examine the potential moderating effect of sex in statistical analyses. Given that age may further complicate the relationship between sex and health outcomes, researchers may also need to consider potential two-way interactions between sex and age.

Race/Ethnicity

Race/ethnicity is another unmodifiable variable that researchers may want to consider when examining the complex relationship between health behaviors and chronic disease risk. Data consistently indicate that race/ethnicity correlates with a variety of health behaviors and health outcomes. For example, CVD-mortality rates vary by race, with non-Hispanic white versus non-Hispanic black males experiencing CVD-mortality rates of 271.9 and 352.4 per 100,000, respectively, and non-Hispanic white versus non-Hispanic black females experiencing CVD-mortality rates of 188.1 and 248.6 per 100,000, respectively (Mozaffarian et al., 2015). The prevalence of at least one CVD risk factor also varies by race/ethnicity, with non-Hispanic black adults demonstrating the highest prevalence of at least one CVD risk factor (58%), and both non-Hispanic whites and Hispanics demonstrating significantly lower prevalence rates of at least one CVD risk factor (47% and 45%, respectively) (Fryar et al., 2012).

Hypertension likely explains non-Hispanic blacks' higher prevalence rates of at least one CVD risk factor, because non-Hispanic black males and females demonstrate the highest HTN prevalence rates (44.9% and 46.1%, respectively) (Crim et al., 2012; Mozaffarian et al., 2015). In contrast, HTN prevalence rates in non-Hispanic white males and females are 32.9% and 30.1%, respectively, and prevalence rates in Hispanic males and females are 29.6% and 29.9%, respectively (Crim et al., 2012; Mozaffarian et al., 2015). Non-Hispanic blacks develop HTN earlier in life and exhibit significantly higher average blood pressure values than non-Hispanic whites (Mozaffarian et al., 2015; Voors, Webber, & Berenson, 1979, 1980). Along with differing HTN prevalence rates between non-Hispanic blacks and other races/ethnicities, these rates also vary between Hispanics of different descent. For example, HTN prevalence rates among Hispanic males range from 19.9% in South America to 32.6% in the Dominican Republic, and prevalence rates among Hispanic females range from 15.9% in South America to 29.1% in Puerto Rico (Daviglus et al., 2012; Mozaffarian et al., 2015). The negative health effects of HTN also vary by race/ethnicity, and non-Hispanic blacks experience a significantly greater negative effect of HTN on stroke risk than do non-Hispanic whites (Howard et al., 2011; Mozaffarian et al., 2015). HTN-related mortality rates are highest in non-Hispanic black males and females (47.1 and 35.1 per 100,000,

respectively) and lowest in non-Hispanic white males and females (17.6 and 15.2 per 100,000, respectively) (Mozaffarian et al., 2015). When considering various CVD risk factors, race/ethnicity appears to be particularly important with regard to the prevalence and negative health effects of HTN.

Racial/ethnic differences also exist in the prevalence of type 2 DM and metabolic syndrome. American Indians/Alaska Natives have the highest DM prevalence rates, with rates of 14.9% and 15.3% among males and females, respectively (Centers for Disease Control and Prevention, 2019b). Non-Hispanic blacks exhibit significantly higher DM prevalence rates than non-Hispanic whites (15.4% and 8.6%, respectively), and Hispanics exhibit significantly higher DM prevalence rates than non-Hispanic whites (11.6% and 8.6%, respectively) (Mozaffarian et al., 2015). The risk of being diagnosed with DM varies by race/ethnicity, with non-Hispanic whites experiencing the lowest risk, and Asian Americans, Hispanic/Latinos, and non-Hispanic blacks experiencing 18%, 66%, and 77% greater risks of a DM diagnosis, respectively (Centers for Disease Control and Prevention, 2019b; Mozaffarian et al., 2015).

Hispanics have significantly higher prevalence rates of metabolic syndrome (40-46% higher) than non-Hispanic whites and blacks (Beltran-Sanchez et al., 2013; Mozaffarian et al., 2015). Non-Hispanic black males demonstrate the lowest and Hispanic males demonstrate the highest metabolic syndrome prevalence rates (18.99% and 34.76%, respectively) (Beltran-Sanchez et al., 2013; Mozaffarian et al., 2015). Asian Indians, American Indians, and Alaska Natives exhibit high prevalence rates of metabolic syndrome, with estimates in Asian Indians ranging from 26.8% to 38.2%, depending on the definition used (Misra et al., 2010; Mozaffarian et al., 2015). Prevalence rates in American Indians are 43.2% and 47.3% among males and females, respectively, and prevalence rates in Alaska Natives are 26.5% and 31.2% among males and females, respectively (Mozaffarian et al., 2015; Schumacher et al., 2008). Racial/ethnic differences also exist regarding the health consequences of metabolic syndrome, differences that may be related to genetic factors (Beltran-Sanchez et al., 2013; Mozaffarian et al., 2015). For example, when considering the presence of non-alcoholic fatty liver disease (NAFLD) among people with metabolic syndrome, only 18% of non-Hispanic blacks have NAFLD, whereas, 39% of Hispanics have NAFLD (Mozaffarian et al., 2015; Tota-Maharaj et al., 2014).

Obesity prevalence rates in the U.S. vary by race/ethnicity (Hales et al., 2017). Non-Hispanic Asians have significantly lower obesity prevalence rates (12.7%) than other racial/ethnic groups, and non-Hispanic whites have significantly lower obesity prevalence rates (37.9%) than non-Hispanic blacks and Hispanics (46.8% and 47.0%, respectively) (Hales et al., 2017). Racial/ethnic differences in obesity prevalence rates also vary within the sexes. For example, non-Hispanic Asian males have significantly lower obesity prevalence rates (10.1%) than all other male racial/ethnic groups (Hales et al., 2017). Within males, non-Hispanic blacks and whites have significantly lower obesity prevalence rates (37.9% and 36.9%, respectively) than Hispanics (43.1%) (Hales et al., 2017). Among females, non-Hispanic Asians have the lowest obesity prevalence rates (14.8%) compared to females in all other racial/ethnic groups, and non-Hispanic black and Hispanic females have significantly higher obesity prevalence rates (54.8% and 50.6%, respectively) than non-Hispanic white females (38.0%) (Hales et al., 2017).

In contrast to adults, non-Hispanic white children do not have higher obesity prevalence rates than non-Hispanic Asian children; however, non-Hispanic black and Hispanic children have significantly higher obesity prevalence rates (22.0% and 25.8%, respectively) than non-Hispanic white (14.1%) and Asian (11.0%) children (Hales et al., 2017). Similar to adults, racial/ethnic differences in obesity prevalence rates among children vary within the sexes. Specifically, Hispanic male children have significantly higher obesity prevalence rates (28.0%) than non-Hispanic white, black, and Asian males (14.6%, 19.0%, and 11.7%, respectively) (Hales et al., 2017). Racial/ethnic differences in obesity prevalence rates in female children mirror those among all children, with non-Hispanic black and Hispanic females having significantly higher obesity prevalence rates (25.1% and 23.6%) than both non-Hispanic white and non-Hispanic Asian females (13.5% and 10.1%, respectively) (Hales et al., 2017). Clearly, racial/ethnic differences exist regarding obesity prevalence rates in adults and children.

Self-reported PA data suggest that a larger proportion of non-Hispanic white adults meet PA guidelines (53.4%) compared to either non-Hispanic black (41.4%) or Hispanic adults (42.9%) (Mozaffarian et al., 2015). Adolescent data mirror these findings, with 28.2% of non-Hispanic whites meeting PA guidelines, compared to 26.3% of non-Hispanic blacks and 25.5% of Hispanics (Kann et al.,

2014; Mozaffarian et al., 2015). Physical inactivity rates in adults and children mirror PA data, with 27.0% of non-Hispanic white adults reporting being inactive, compared with 39.7% and 38.8% of Hispanics and non-Hispanic blacks, respectively (Mozaffarian et al., 2015). Similarly, among children, 16.1%, 20.3%, and 27.3% of non-Hispanic white, black, and Hispanic females report being physically inactive, respectively (Kann et al., 2014; Mozaffarian et al., 2015). Among male children, 9.2%, 12.1%, and 15.2% of non-Hispanic whites, blacks, and Hispanics report being physically inactive, respectively (Kann et al., 2014; Mozaffarian et al., 2015). In adults, Hispanic adults of all ages spend less time in SB than non-Hispanic whites or blacks, and Hispanic males ages 20-39 years old spend the least amount of time in SB among all adults (5.98 hours/day) (Matthews et al., 2008). However, race/ethnicity does not appear to be related to the amount of time children spend in SB, with the exception of girls ages 6-11 years old, in which case, non-Hispanic black females are less sedentary (5.88 hours/day) than either non-Hispanic white (6.18 hours/day) or Hispanic (6.02 hours/day) females (Matthews et al., 2008).

Despite a lack of racial/ethnic differences in time spent in SB among children, differences do appear to exist when considering specific sedentary behaviors, including computer and television use. For example, non-Hispanic black male and female children exhibit the highest prevalence rates of spending at least three hours per day in non-school related computer use (51.9% and 46.6%, respectively), with slightly lower rates among Hispanic males and females (42.0% and 44.8%, respectively), and the lowest rates among non-Hispanic white males and females (39.1% and 35.6%, respectively) (Kann et al., 2014; Mozaffarian et al., 2015). Non-Hispanic black male and female children report the highest prevalence rates of watching television for at least three hours per day (55.3% and 52.2%, respectively), with Hispanic males and females reporting slightly lower levels (36.5% and 39.0%, respectively), and non-Hispanic white males and females reporting the lowest levels of television use (25.7% and 24.3%, respectively) (Kann et al., 2014; Mozaffarian et al., 2015).

The relationship between PA and health outcomes also appears to vary by race. Specifically, the most active non-Hispanic blacks (≥ 32.32 MET-hours/day) have 24%, 19%, and 24% lower risks of all-cause mortality, CVD mortality, and cancer mortality, respectively, than do the least active non-Hispanic

blacks (<9.73 MET-hours/day) (Matthews et al., 2014). In contrast, the most active non-Hispanic whites only demonstrate significantly lower risk of all-cause mortality (HR = 0.76) and CVD mortality (HR = 0.69), but not cancer mortality, compared to the least active non-Hispanic whites (Matthews et al., 2014). When considering sex and race in combination, results also vary. The most active non-Hispanic black males exhibit lower HRs for CVD mortality and cancer mortality compared to the least active non-Hispanic black males (HR = 0.71 and 0.76, respectively) (Matthews et al., 2014). In contrast, among non-Hispanic black females, those in the most active group do not demonstrate significantly lower HR for CVD mortality and cancer mortality than the least active non-Hispanic black females (HR = 1.05 and 0.81, respectively) (Matthews et al., 2014).

Race/ethnicity may not affect the relationship between SB and all-cause mortality. One study examining SB (represented by total time per day spent sitting) found that, when comparing the most sedentary adults (>12 hours/day) to the least sedentary adults (<5.76 hours/day), the HRs for all-cause mortality were 1.19 and 1.24 for non-Hispanic black and non-Hispanic white adults, respectively (Matthews et al., 2014). Importantly, these relationships existed even after controlling for PA level (Matthews et al., 2014). However, this study also examined the combined effects of PA and SB on all-cause mortality risk, and they found that the most sedentary and least active non-Hispanic blacks (≥10.5 hours/day sitting; <12.6 MET-hours/day) had a 47% greater all-cause mortality risk (HR = 1.47) compared to the least sedentary and most active non-Hispanic blacks (<6.5 hours/day sitting; ≥26.4 MET-hours/day) (Matthews et al., 2014). Researchers also found that, when comparing the least versus the most sedentary adults (>12 hours/day SB vs. <5.76 hours/day SB), non-Hispanic black females showed a stronger association between SB and all-cause mortality than did non-Hispanic black males (HR = 1.27 and 1.13, respectively) (Matthews et al., 2014). However, no sex differences existed among non-Hispanic blacks regarding the association between SB and either CVD mortality or cancer-mortality (Matthews et al., 2014). In contrast, among non-Hispanic whites, a strong positive association existed between SB and CVD mortality in males (HR = 2.18), but not in females (data not provided) (Matthews et al., 2014).

Finally, racial/ethnic differences exist in the associations between total time spent in SB and cardiometabolic health outcomes. Total sedentary time negatively correlates with WC in non-Hispanic whites, whereas, no correlation exists in Hispanics, and a positive correlation exists in non-Hispanic blacks (Healy et al., 2011). In contrast, significant detrimental associations exist between total sedentary time and insulin among all racial/ethnic groups; however, the overall shape of the associations between total time spent in SB and insulin differs by race/ethnicity (Healy et al., 2011). The relationship between breaks in SB and cardiometabolic health outcomes only appear to vary by race/ethnicity for HDL-cholesterol, in which case, breaks are significantly and positively associated with HDL-cholesterol in non-Hispanic whites, but no association exists for Hispanics or non-Hispanic blacks (Healy et al., 2011).

Similar to age and sex, race/ethnicity clearly relates to health behaviors and chronic disease, affecting prevalence rates and the relationships between health behaviors and chronic disease. As such, researchers should include race and ethnicity as variables in statistical models and should examine the potential moderating effects of race and ethnicity on the relationships between health behaviors and outcomes. Additionally, race or ethnicity may further complicate the relationship between age, sex, and health outcomes, suggesting the potential need for considering three-way interactions between race/ethnicity, sex, and age.

Overall, the unmodifiable characteristics of age, sex, and race/ethnicity represent important correlates and/or predictors of health behaviors (i.e. PA, SB), chronic disease risk, and the relationships between health behaviors and outcomes. Researchers often include these unmodifiable characteristics as control variables in statistical models, instead of examining the main effects of these variables on outcomes. Controlling for unmodifiable variables instead of examining their main effects can potentially result in misleading or inaccurate findings. Failing to consider these unmodifiable variables as potential moderators of the relationships between health behaviors and outcomes could lead to inaccurate findings, particularly if moderation does exist, since the presence of moderation can make it seem as though a variable has no main effect on outcomes. For example, if breaks in SB only affect CVD risk in females but not males, simply examining the main effects of sex, rather than examining it as a moderator, will

likely result in researchers misinterpreting sex as an insignificant variable in statistical models. Researchers with appropriate statistical knowledge and substantive expertise regarding the role of these unmodifiable variables in affecting health behaviors and health outcomes are capable of examining the main and/or moderating effects of age, sex, and race/ethnicity on the relationships between health behaviors and outcomes. Such modeling will allow researchers to tease out the varying effects of these unmodifiable characteristics, which will allow a more in-depth understanding of how health behaviors relate to chronic disease. This in-depth understanding has the potential to positively affect future research studies, inform the appropriate tailoring of interventions to improve health behaviors and associated health outcomes, and inform clinical and/or public health recommendations, all of which can help improve human health outcomes.

CHAPTER 3 – TECHNOLOGY AND COMPUTER SCIENCE

Extracting meaningful knowledge from data represents a primary goal of data scientists. Achieving this goal requires skills for managing, cleaning, and quality assuring data. Each of these tasks requires a substantial amount of time and energy, and data management represents a large part of what data scientists do, with research suggesting they use approximately 80% of their time finding, cleaning, and/or organizing data (Bowne-Anderson, 2018; Crowdflower, 2016). Properly managing and cleaning data is particularly important to ensure that outcomes can be trusted (Bowne-Anderson, 2018). Data scientists also require an understanding of how to capitalize on the use of technology. For example, using accelerometers for capturing information about individuals' 24-hour movement patterns, including their time spent in PA, SB, or sleeping. Researchers can also use smartphones to capture repeated measures of individuals' psychosocial predictors of health behaviors, such as stress, in real-time and in their natural environment. The studies in this chapter provide examples of how to use technology and computer science to enhance data management and the quality control and assurance of health-related data, as well as how to use technology to measure individuals' health behaviors. Study 1 demonstrates how to migrate an existing research study from paper-based data collection to the Research Electronic Data Capture system (P. A. Harris et al., 2009), using the example of an ongoing, longitudinal program in firefighters that includes measures of psychosocial determinants of health, cardiorespiratory and musculoskeletal fitness, and cardiovascular disease risk. It also demonstrates how electronic data capture is an efficient tool for enhancing the management and quality control and assurance of research studies. Study 2 demonstrates the utility of the activPAL monitor (PAL Technologies Ltd., 2010) to measure individuals' time spent lying down (a proxy for sleep) in comparison to self-report or an alternative algorithm.

Study 1 – Migration of an ongoing, community-based project in firefighters to the Research Electronic Data Capture (REDCap) platform

Introduction

Until recently, researchers traditionally used paper-based data capture; however, there are inherent risks and limitations associated with this approach, including missing or lost data (Cummings & Masten, 1994; Reynolds-Haertle & McBride, 1992). Data can be missing if participants fail to answer questions, and data can be lost due to participant or researcher errors (Cummings & Masten, 1994). Data entry or coding errors can occur when transferring paper-based data into an electronic database (Reynolds-Haertle & McBride, 1992; Weber & Roberts, 2000). Time and cost limitations also exist, with personnel spending substantial time transferring paper-based data into electronic databases and double-entering data to improve accuracy and reduce errors (Reynolds-Haertle & McBride, 1992; Weber & Roberts, 2000; Weber, Yarandi, Rowe, & Weber, 2005). These tasks require substantial manpower, thereby increasing the costs associated with paper-based data capture (Reynolds-Haertle & McBride, 1992; Weber & Roberts, 2000; Weber et al., 2005). Finally, employing a paper-based data capture approach can increase the risk for breaches of privacy and confidentiality (Weber et al., 2005).

Using electronic data capture (EDC) for capturing and managing data ameliorates many of the inherent risks and limitations of paper-based data capture and leads to improved efficiency, accuracy, and cost savings (Dunn, Cobb, Levey, & Gutman, 2016; Helms, 2001; Litchfield et al., 2005; Prokscha, 2012; Shah et al., 2010; Velikova et al., 1999; Weber & Roberts, 2000; Weber et al., 2005). EDC reduces the risk of missing data by requiring responses for individual items (Dunn et al., 2016; Shah et al., 2010; Velikova et al., 1999; Weber & Roberts, 2000; Weber et al., 2005). EDC often includes real-time data checks to identify invalid or out of range values for a given variable, decreasing the likelihood of data entry errors (Dunn et al., 2016; Shah et al., 2010; Velikova et al., 1999; Weber & Roberts, 2000; Weber et al., 2005). EDC abrogates the risk for data coding errors because data are automatically coded, and there is no loss of data due to data transfer from paper to an electronic database (Dunn et al., 2016; Shah et al., 2010; Velikova et al., 1999; Weber & Roberts, 2000; Weber et al., 2005). EDC reduces the time required

for data capture and management because there is no need for double-data entry when using real-time EDC, thereby concomitantly decreasing the number of staff required to manage data (Weber et al., 2005). Finally, although EDC requires higher start-up costs associated with developing, testing, and deploying EDC forms, maintenance costs for EDC are much smaller than paper-based approaches (Dunn et al., 2016; Prokscha, 2012; Weber et al., 2005). As such, the average total cost for using EDC is smaller than paper-based approaches, particularly as the number of participants in the study increases (Dunn et al., 2016; Prokscha, 2012; Weber et al., 2005).

A wide range of EDC systems exist to support data capture, management, and analyses (Dunn et al., 2016; Leroux, McBride, & Gibson, 2011; Shah et al., 2010). These systems are often expensive, which can preclude academic researchers from using them (Dunn et al., 2016; Leroux et al., 2011; Shah et al., 2010); however, the Research Electronic Data Capture (REDCap) platform developed by Harris and colleagues at Vanderbilt University is available to academic research institutions across the world, either for free or at a low cost (P. A. Harris et al., 2019; P. A. Harris et al., 2009). Over 3200 institutions in 128 countries use REDCap, and it has been used in a variety of contexts, including basic science research, clinical trials, and cohort studies, among others (P. A. Harris et al., 2019). REDCap confers many advantages to researchers, with features including collaboration across institutions, role-based security restrictions, quality assurance mechanisms, data exports for statistics packages, and customized reporting, among other things (P. A. Harris et al., 2009; Obeid et al., 2013). REDCap supports cross-sectional, longitudinal, and multi-armed studies, is HIPAA compliant, and is recognized by institutional review boards as a secure approach for capturing and storing data (Dunn et al., 2016; P. A. Harris et al., 2019; P. A. Harris et al., 2009; Obeid et al., 2013). These features of REDCap, and that it is supported by our institution, resulted in us adopting REDCap to support the Firefighter Testing Program (FTP) at Colorado State University.

The FTP is an ongoing, longitudinal project that started twenty years ago for the purposes of assessing firefighters' fitness and their cardiovascular disease risk. The FTP also informs research regarding the relationships between firefighters' fitness, psychosocial outcomes, and cardiovascular

disease risk. The FTP is a longitudinal study with a large number of participants, has unique data needs (including real-time data capture, participant-completed surveys, and manual data entry), and involves a large number of personnel. The FTP also requires a quick and convenient mechanism for providing reports to individual firefighters and fire departments. Finally, multiple researchers using a variety of statistical software programs require easy access to the data. As such, we determined that the FTP could benefit in migrating from paper-based data capture to EDC in the REDCap platform.

The objectives of this paper are to describe the process for establishing a REDCap project that: 1) provides an efficient tool for collecting data via real-time EDC, participant surveys, and manual data entry; 2) accommodates delivering individual reports to firefighters and aggregate reports to fire departments; and 3) facilitates research to examine the relationships between firefighters' fitness, psychosocial outcomes, and cardiovascular disease risk. We will also provide recommendations to REDCap users based on lessons learned during the migration.

Methods

Data Description

The FTP is an ongoing project that includes firefighters from departments in Colorado and Wyoming. Fire departments vary regarding how often firefighters complete testing and the specific measures they require firefighters to complete. Comprehensive testing includes measures of fitness (VO2max treadmill tests, strength, flexibility, etc.), body fatness (skinfolds, waist circumferences, etc.), cardiovascular disease risk (family history, blood work, etc.), and psychosocial health (depression, anxiety, etc.). In any given year, firefighters may complete any or all of the measures above, with the time lapse between visits varying by department.

When we started developing the FTP REDCap project, 1632 firefighters had been tested, with data for 1153 firefighters stored in an SPSS file, and the remaining 479 firefighters' data stored in paper files. Firefighters provided written, informed consent, and the project was approved by the CSU Institutional Review Board.

REDCap Project Development

Project development required multiple steps including: 1) creating a new REDCap project; 2) developing data collection instruments with specified fields and field formatting; 3) creating calculated fields to support data reporting and research needs (i.e. classifying participants' cardiovascular disease risk); 4) developing individual and departmental reports that synchronized with custom formatted Excel files; 5) testing data entry forms, automated electronic surveys, and calculations; 6) configuring user roles and rights; 7) moving the project to production status; 8) importing existing data into the project, and 9) editing the project based on feedback from personnel and participants.

Results

Structure of REDCap Project

The FTP REDCap project was designed as a longitudinal project with a maximum of 20 visits per participant. The project includes 27 forms with 3068 fields (Figure 1). Five forms were enabled as automated electronic surveys (see Figure 1). Three forms were used for real-time EDC, including the Preliminary Evaluation, Preliminary Exercise Prescription Questions, and Treadmill Test forms.

The remaining sixteen forms were used for manual data entry. Seven of these forms were used to enter previously collected data and support future data collection including the Visit Information, Consent, Pulmonary Testing, Hydro DEXA, Blood Work, Heart Event, and Died/Retired/Gone forms. Nine of these forms were used to enter previously collected data that were eliminated from the ongoing FTP protocol, including the Health History Questionnaire (HHQ) Data Entry, Depression Scale Original, Hope Scale, Anger Scale, Hostility and Cynicism Scale, Type A Scale, Forgiveness Scale, Social Support Scale, and Orientation to Life Scale forms. Three forms were developed to calculate scores used in reporting outcomes to firefighters and departments, as well as for calculating values of interest for researchers (Survey Scoring, Cooper – Coronary Risk Profile, and Department Report Calculations forms).

Data Security

We used REDCap's role-based security restrictions to customize data access rights based on a given user's role (Figure 2) (P. A. Harris et al., 2009). The project developer received full rights to the project, with the exception of Record Locking Customization and API. FTP Personnel had similar rights to the project developer; however, they could not edit the project, create data access groups, lock/unlock records, etc. Data Entry Personnel received the fewest rights, limited to running reports, accessing the file repository, executing data quality rules, and creating new records.

Enhanced Data Quality Control

The FTP REDCap project enhanced data quality control measures compared to the previous paper-based approach. We developed field validation settings using previously collected data to identify reasonable validation ranges, thereby reducing data entry error and enhancing data quality.

We re-structured some fields to increase consistency across visits. Repeated measures of demographic and HHQ data in the original database revealed inconsistencies in participants' reporting of key information, such as age and years in the fire service. These inconsistencies reduced the coherency and usability of data, informing the decision to modify existing questions. For example, the original question about years in the fire service, asking participants their "number of years in the fire service", was changed to "What age were you when you started working in the fire service", as it was considered easier for participants to recall the age they started in the fire service, rather than the year they started or total number of years served. A similar approach was used for assessing the use of tobacco products, including years of tobacco use, and years since quitting use.

Enhanced Data Collection Efficiency

Migrating to REDCap enhanced data collection efficiency by allowing real-time EDC by data entry personnel and participants (via automated surveys), abrogating the need to transfer paper data into REDCap. Automated surveys enhanced FTP personnel's ability to quickly screen participants for potential risks associated with completing testing. For example, personnel used survey data to screen participants for medication use and orthopedic injuries to determine if they could safely complete testing.

The automated surveys ensured that participants completed all required questions and forms; whereas, previously, personnel had to examine paper surveys to identify potentially missing data. The development of calculated fields removed the need to calculate scores by hand or in other software programs, reducing the risk for error and increasing efficiency for providing reports to firefighters/departments and results for researchers.

Supporting Reporting Needs

The project included customized reports developed using REDCap's Data Exports, Reports, and Stats module (P. A. Harris et al., 2009). These reports allowed personnel to export the specific data needed for reports to individual firefighters or fire departments. Individual reports were filtered by ID number, and fire department reports were filtered by department and year to provide aggregate data for those firefighters tested in a given year. Reports were exported to compatible Excel files that were formatted to meet individual/departmental reporting needs.

Supporting Research Needs

The project supported research needs by enhancing the ability to easily categorize and analyze data. Fields that previously used qualitative responses were converted to categorical fields. For example, a question about history of hospitalizations and surgeries was converted from a qualitative response to a checkbox field with multiple categories, including heart-related hospitalizations/surgeries, elective surgeries, orthopedic surgeries, etc. (Figure 3). Branching logic was then used to capture additional information about specific surgeries, such as the type of orthopedic surgery (i.e. ACL repair, Spinal/back surgery, broken bone, etc.), location of surgery (i.e. right knee, left shoulder, etc.), length of time since the surgery occurred, etc. Another example was converting the questions about family history of heart disease, diabetes, etc., to categorical checkboxes that included only first degree relatives (father, mother, brother, sister, daughter, son), thereby preventing participants from providing unnecessary information about family members who were not first degree relatives (Figure 4). This was particularly important for assessing cardiovascular disease risk, which is determined, in part, based on the health history of first-degree relatives.

Discussion

We successfully migrated the existing FTP to a REDCap project that provided efficient data collection tools, accommodated individual and departmental reporting needs, and facilitated achieving research goals. Building the REDCap project required an iterative process to design, test, and edit fields (Dunn et al., 2016; P. A. Harris et al., 2009; REDCap, 2020). We hope that the process and lessons learned throughout this migration process will benefit other researchers attempting to transition to EDC but who are struggling to do so due to typical barriers or fear of losing data (Dunn et al., 2016; Franklin, Guidry, & Brinkley, 2011; Shah et al., 2010).

Existing data informed the project design by enhancing the efficiency of collecting, entering, and analyzing data. For example, we changed qualitative fields to categorical fields to improve the ease of data entry and to facilitate data analyses. These changes required substantial time and consideration to recode qualitative responses to categories that accurately reflected the existing data and provided reasonable options for future data collection. This also required researchers to recode legacy data prior to import. Other researchers who are considering migrating an existing project to REDCap should be aware that identifying appropriate categories and recoding data is potentially one of the most time-consuming aspects of project migration.

Successfully creating a REDCap project that was efficient for FTP personnel required field-testing and subsequent edits; for example, changing validation ranges to reduce the frequency of 'Out of Range' error messages popping-up during real-time EDC. During the first few months of field-testing, personnel simultaneously used EDC and paper-based data collection to ensure no loss of data, such as when collecting data in different environments (i.e. university testing facility versus fire stations). Field-testing resulted in multiple edits, with some requiring subsequent exporting and re-importing of data. Importantly, making edits after putting a REDCap project into production often requires the local REDCap administrator's approval, which can help safeguard users against the unintended loss or recoding of data (REDCap, 2020). Unfortunately, this can limit users' ability to quickly edit a project to improve functionality. The institution hosting REDCap determines which changes do or do not require

administrator approval, with our institution using the most permissive option (Personal communication – Amanda Miller, 2020). However, despite our institution's permissive approach, administrator approval hindered our ability to quickly respond to FTP personnel needs. Indeed, requiring approval for post-production edits was problematic because of the FTP's rapid, ongoing data collection needs, and the large number of participants in the FTP. Other REDCap users may encounter similar challenges when making post-production edits and should, if possible, test projects with sham participants/data to inform changes prior to moving the project into production (Dunn et al., 2016; P. A. Harris et al., 2009; REDCap, 2020).

Transitioning to automated surveys improved convenience for participants and dramatically reduced the time required for survey completion. The use of branching logic saved time by allowing participants (and data entry personnel) to bypass irrelevant questions. Additionally, anecdotal feedback from participants indicated they preferred answering surveys via REDCap, rather than via pen-and-paper, specifically due to the convenience and efficiency of completing the surveys electronically, similar to findings from other studies who migrated from paper-based data capture to EDC (Dunn et al., 2016; Helms, 2001; Litchfield et al., 2005).

Using calculated variables in REDCap helped accommodate reporting needs and research goals by ensuring that all calculations were consistent between participants, which is a strong advantage of REDCap noted by other researchers (Dunn et al., 2016). Additionally, REDCap's Data Quality Rule H ensured that, if changes to calculations were made, it was easy to recalculate the value for all participants in the database (Dunn et al., 2016; P. A. Harris et al., 2009). This was more efficient than calculating (or recalculating) values outside of REDCap and reduced the risk for calculation errors (Dunn et al., 2016). REDCap users should note that creating calculated variables in REDCap can be challenging, particularly when using a large number of logic statements. For example, the FTP requires calculating scores based on age- and sex-specific norms, thereby requiring a large number of if/then statements, and we determined it was easier to create multiple, sequential calculations to determine the final age-/sex-specific score. While such calculations may be easier to complete using statistical software, calculating said values in REDCap created an easy workflow that helped accommodate the FTP's reporting needs. Despite some challenges

in creating the calculations, we recommend that REDCap users migrating from a paper-based project to REDCap create calculated variables within REDCap to ensure consistency of calculations, increase efficiency, and reduce error (Dunn et al., 2016; Helms, 2001; Litchfield et al., 2005; Shah et al., 2010; Velikova et al., 1999).

While we achieved many of our goals when migrating to REDCap, we identified inconsistencies in participants' reporting of variables across visits, and we could not successfully address these inconsistencies within REDCap. We specifically identified inconsistencies in variables that should not change, such as race/ethnicity, suggesting the need to reconsider our data collection approach. We attempted to use REDCap's Smart Variable feature to pull forward data from a participant's most recent visit, or another specified visit, into the same data field for a subsequent visit (REDCap, 2020). Smart Variables allow participants to see their prior answers and modify them when needed (REDCap, 2020), which should reduce inconsistencies and decrease participant burden. However, in our case, using Smart Variables was incompatible with the FTP. Variability in how often firefighters completed testing, as well as which measures they completed a given visit, precluded the use of Smart Variables, because we could not prevent REDCap from pulling forward data into a visit for which no data were collected. For example, a participant might complete the HHQ on visits 1 and 4, but the Smart Variable pulled visit 1 data into visits 2 and 3, thereby misrepresenting which data were actually collected. In such cases, this also meant that the HHQ data pulled forward from visit 1 into visit 4 could be quite old, but there was no guarantee that participants would modify their HHQ data for visit 4. Indeed, prior to migrating to REDCap, participants were allowed to modify previously completed paper-based HHQs; however, many participants failed to update important fields (i.e. medication use, hospitalizations), supporting our concern that they might fail to update their data. These specific challenges in using the Smart Variables for the FTP REDCap project precluded our using them for the majority of fields. However, we did use Smart Variables for fixed characteristics, like date of birth, biological sex, and race/ethnicity.

While Smart Variables were often incompatible with the FTP REDCap project, this was likely due to the unique nature of the FTP, and we suggest that, in many cases, REDCap users would be wise to

use Smart Variables, because they can reduce participant burden and/or data entry workload. For fixed-characteristics, such as date of birth, pulling forward data from visit 1 into subsequent visits is appropriate to reduce participant burden and decrease data processing workload. However, researchers should critically consider which variables are fixed versus changeable, and avoid making changeable variables into Smart Variables. For example, marital status is a commonly collected demographic characteristic that is changeable, though changes in marital status may occur rarely. REDCap users should avoid Smart Variables in such cases, as pulling forward data from prior visits introduces the risk that participants may not modify their answers, resulting in unintended error. This is particularly necessary for longitudinal projects in which visits may occur only once every few years.

REDCap Limitations

We did experience some REDCap limitations worth noting. Regarding surveys, REDCap will mark a survey as 'complete' if a participant fills out all of the visible fields. However, if the survey includes hidden fields for the researcher to fill out, REDCap will mark the survey as complete, even if the hidden fields are not filled out. This can result in confusion about which forms are truly 'complete', potentially leading to missing data. This limitation can be partially mitigated by creating reports to show researchers when hidden fields are incomplete, and combining these reports with REDCap's new Alerts and Notifications feature (REDCap, 2020), thereby reducing confusion and the potential for missing data.

Formatting issues when exporting data from REDCap can also create challenges, particularly if researchers need to re-import data due to post-production edits. When exporting numeric fields from REDCap to a .csv file, the exported file automatically removes trailing zeroes after the decimal point, even if the REDCap field requires two decimal places, such that "1.55" exports to "1.55", but "1.00" exports to "1". This requires reformatting the data prior to re-importing it into REDCap so that all numeric values follow a given field's formatting requirements. We acknowledge that many users may not encounter this limitation, due to the rarity of exporting and reimporting data; however, it would be useful if REDCap could force data to be exported in the same format as specified for a given field.

Exporting data from checkbox fields is another limitation, because unchecked boxes are exported as a '0' (REDCap's code for 'unchecked'). This occurs even if the entire form is empty. This automatic exporting of '0' for unchecked boxes can cause users to erroneously believe that a participant completed part of a particular form, and to analyze their data accordingly, even when that '0' is not truly indicative of participant answering 'no'. It would be helpful for REDCap to build a feature that recognizes when there are no data in a given form and, in such a situation, export checkbox fields as blanks instead of zeros. This is particularly important when participants do not complete all of the same assessments, as it can result in mistakenly analyzing data that do not truly exist.

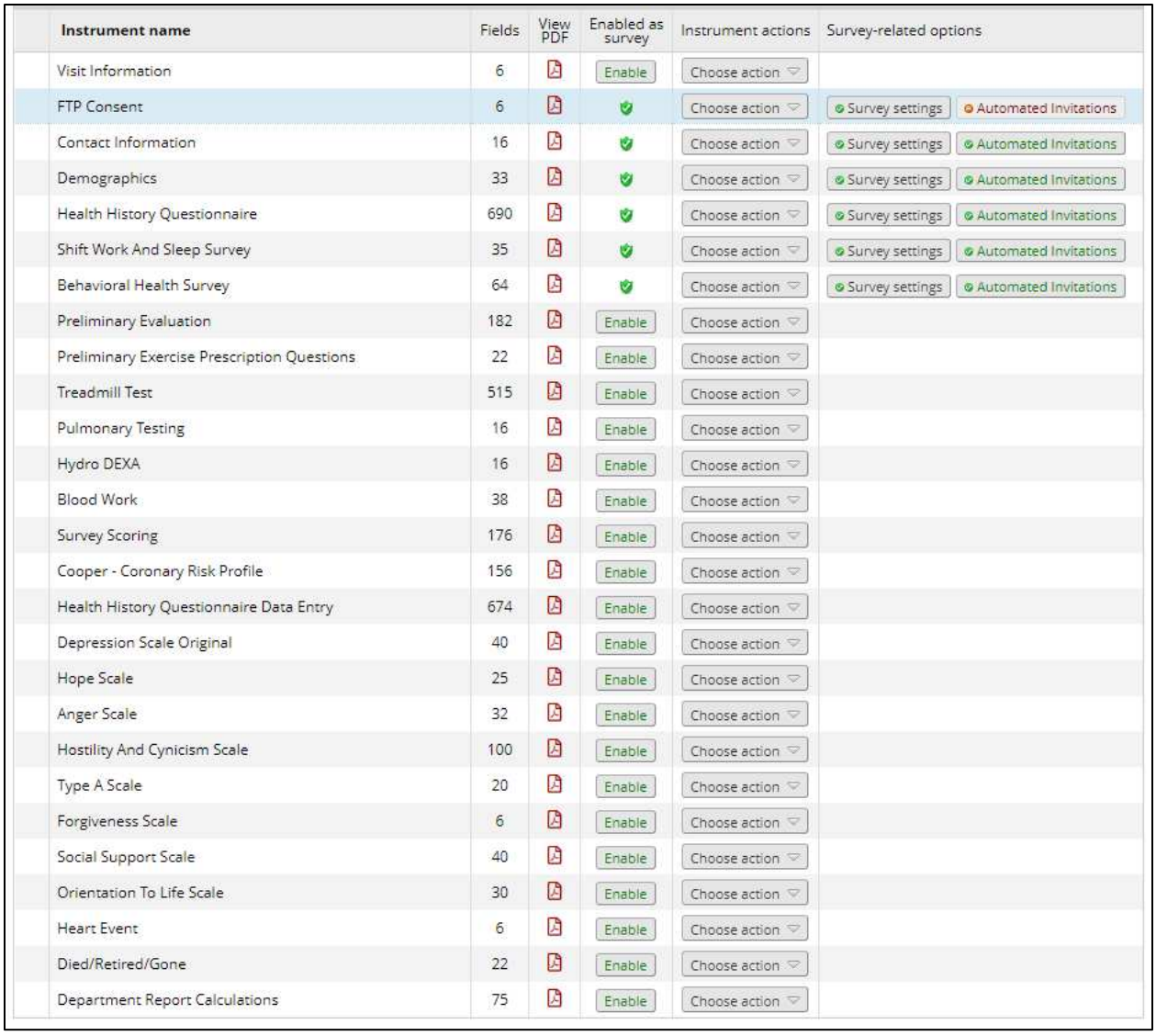
Indeed, we found that REDCap cannot always accommodate longitudinal projects in which participants vary regarding the measures they complete at any given visit. REDCap was designed to support more standard longitudinal projects in which participants complete the same measures for a given visit, allowing researchers to identify which forms should be available for a particular visit (P. A. Harris et al., 2009; REDCap, 2020). REDCap also allows users to create multiple arms in studies and to use branching logic to accommodate variability in which measures are completed by given participants (P. A. Harris et al., 2009; REDCap, 2020). Unfortunately, these features only accommodate systematic variability, typically at the group level, and are insufficient to accommodate more random variability at the individual level. Although branching logic allows users to hide individual fields in a project, it cannot be used to hide entire forms (REDCap, 2020), making it appear as though individual participants failed to complete a particular set of measures. It would be useful for REDCap to create a feature in which entire forms can be hidden. This would be helpful for projects like the FTP, in which there exists large variability regarding the measures individual participants complete at a given visit.

Finally, REDCap's reporting feature can accommodate many reporting needs (REDCap, 2020); however, the reports are not formatted in a user-friendly manner. While this is a minor limitation, researchers who intend to use reports for providing feedback to participants should be aware that they may need to develop reports outside of the REDCap platform that are compatible with REDCap report

data. Custom reports may be particularly necessary if researchers are creating reports for the purpose of educating participants on their study/testing outcomes.

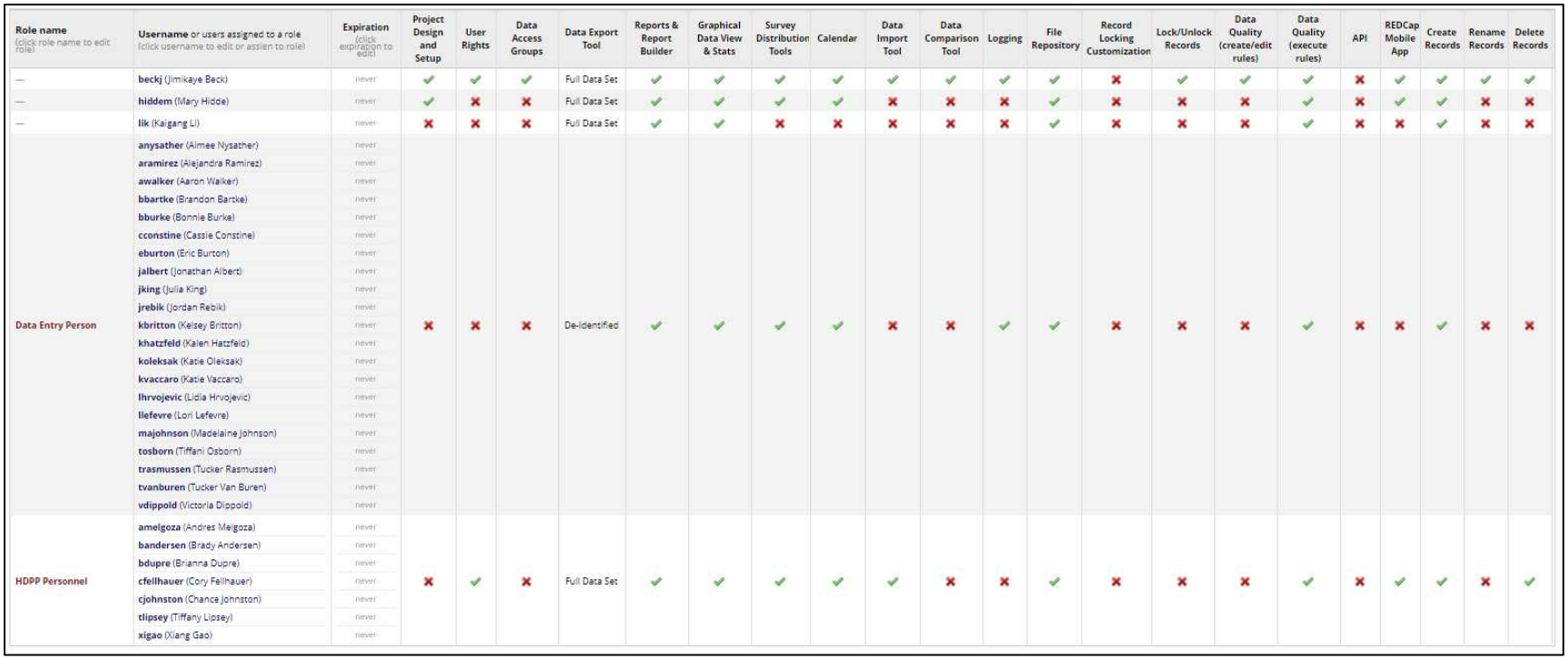
Conclusions

Migrating the FTP to REDCap achieved our data collection, reporting, and research goals. The use of real-time EDC, automated surveys, and branching logic enhanced efficiency for FTP personnel and participants. Using calculated variables improved data quality control and supported reporting and research needs. REDCap failed to fully accommodate handling variability in repeated measures between participants; however, variability in the FTP likely exceeds that of typical research studies. Overall, REDCap was able to support the majority of the FTP's needs, allowing successful migration of the FTP without loss of data, and is a useful tool for helping researchers efficiently capture and manage data.



Instrument name	Fields	View PDF	Enabled as survey	Instrument actions	Survey-related options
Visit Information	6		Enable	Choose action	
FTP Consent	6			Choose action	Survey settings, Automated Invitations
Contact Information	16			Choose action	Survey settings, Automated Invitations
Demographics	33			Choose action	Survey settings, Automated Invitations
Health History Questionnaire	690			Choose action	Survey settings, Automated Invitations
Shift Work And Sleep Survey	35			Choose action	Survey settings, Automated Invitations
Behavioral Health Survey	64			Choose action	Survey settings, Automated Invitations
Preliminary Evaluation	182		Enable	Choose action	
Preliminary Exercise Prescription Questions	22		Enable	Choose action	
Treadmill Test	515		Enable	Choose action	
Pulmonary Testing	16		Enable	Choose action	
Hydro DEXA	16		Enable	Choose action	
Blood Work	38		Enable	Choose action	
Survey Scoring	176		Enable	Choose action	
Cooper - Coronary Risk Profile	156		Enable	Choose action	
Health History Questionnaire Data Entry	674		Enable	Choose action	
Depression Scale Original	40		Enable	Choose action	
Hope Scale	25		Enable	Choose action	
Anger Scale	32		Enable	Choose action	
Hostility And Cynicism Scale	100		Enable	Choose action	
Type A Scale	20		Enable	Choose action	
Forgiveness Scale	6		Enable	Choose action	
Social Support Scale	40		Enable	Choose action	
Orientation To Life Scale	30		Enable	Choose action	
Heart Event	6		Enable	Choose action	
Died/Retired/Gone	22		Enable	Choose action	
Department Report Calculations	75		Enable	Choose action	

Figure 2. Firefighter Testing Program – REDCap project design



Role name (click role name to edit role)	Username or users assigned to a role (click username to edit or assign to role)	Expiration (click expiration to edit)	Project Design and Setup	User Rights	Data Access Groups	Data Export Tool	Reports & Report Builder	Graphical Data View & Stats	Survey Distribution Tools	Calendar	Data Import Tool	Data Comparison Tool	Logging	File Repository	Record Locking Customization	Lock/Unlock Records	Data Quality (create/edit rules)	Data Quality (execute rules)	API	REDCap Mobile App	Create Records	Rename Records	Delete Records
—	**beckj** (Jimikaye Beck)	never	✓	✓	✓	Full Data Set	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✗	✓	✓	✓	✓
—	**hiddem** (Mary Hidde)	never	✓	✗	✗	Full Data Set	✓	✓	✓	✓	✗	✗	✗	✓	✗	✗	✗	✓	✗	✓	✓	✗	✗
—	**lik** (Kaigang Li)	never	✗	✗	✗	Full Data Set	✓	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗	✓	✗	✗	✓	✗	✗
Data Entry Person	**anysather** (Aimee Nysather)	never	✗	✗	✗	De-Identified	✓	✓	✓	✓	✗	✗	✓	✓	✗	✗	✗	✓	✗	✗	✓	✗	✗
	aramirez (Alejandra Ramirez)	never																					
	awalker (Aaron Walker)	never																					
	bbartke (Brandon Bartke)	never																					
	bburke (Bonnie Burke)	never																					
	cconstine (Cassie Constine)	never																					
	eburton (Eric Burton)	never																					
	jalbert (Jonathan Albert)	never																					
	jking (Julia King)	never																					
	jrebik (Jordan Rebik)	never																					
	kbritton (Kelsey Britton)	never																					
	khatzfeld (Kalen Hatzfeld)	never																					
	koleksak (Katie Oleksak)	never																					
	kvaccaro (Katie Vaccaro)	never																					
	lhrvojevic (Lidia Hrvojevic)	never																					
	llefevre (Lori Lefevre)	never																					
	majohnson (Madelaine Johnson)	never																					
	tosborn (Tiffani Osborn)	never																					
	trasmussen (Tucker Rasmussen)	never																					
	tvanburen (Tucker Van Buren)	never																					
	vdippold (Victoria Dippold)	never																					
HDPP Personnel	**amelgoza** (Andres Melgoza)	never	✗	✓	✗	Full Data Set	✓	✓	✓	✓	✓	✗	✗	✓	✗	✗	✗	✓	✗	✓	✓	✗	✓
	bandersen (Brady Andersen)	never																					
	bdupre (Brianna Dupre)	never																					
	cfellhauer (Cory Fellhauer)	never																					
	cjohnston (Chance Johnston)	never																					
	tlipsey (Tiffany Lipsey)	never																					
	xigao (Xiang Gao)	never																					

Figure 3. Customized user roles

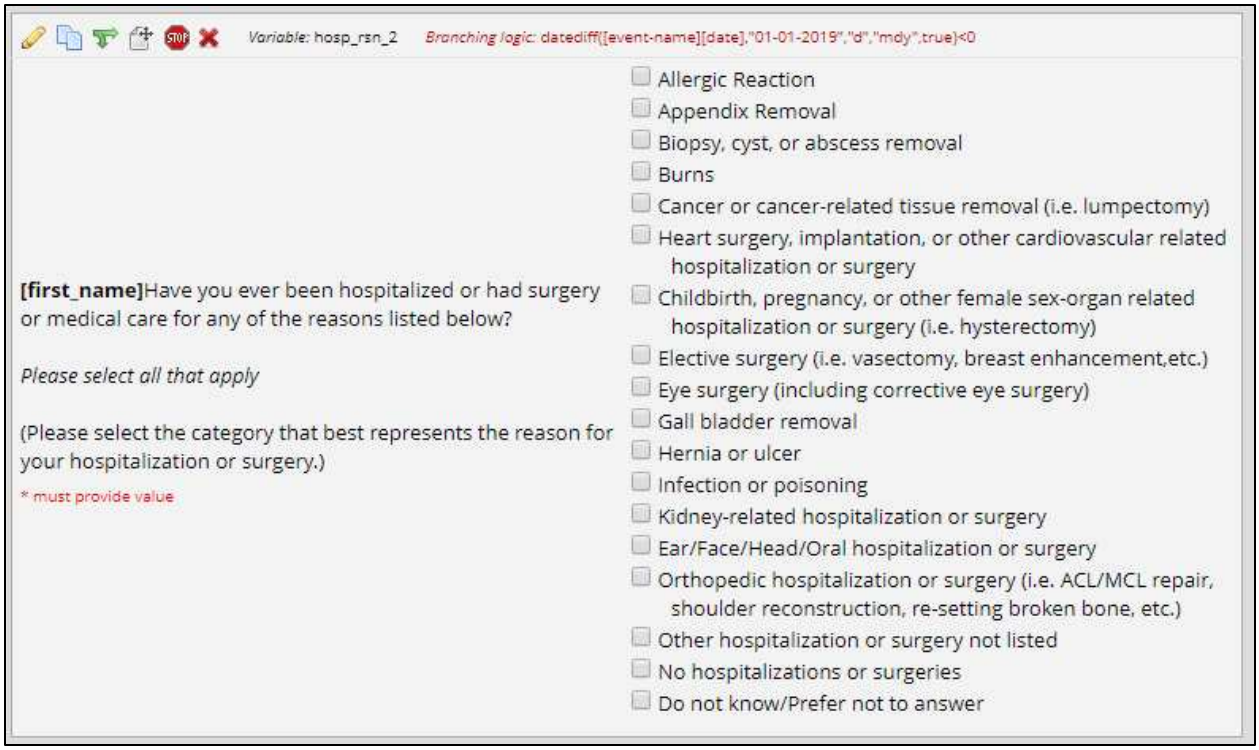


Figure 4. Hospitalizations/Surgeries – Converted from qualitative field to categorical/checkbox field

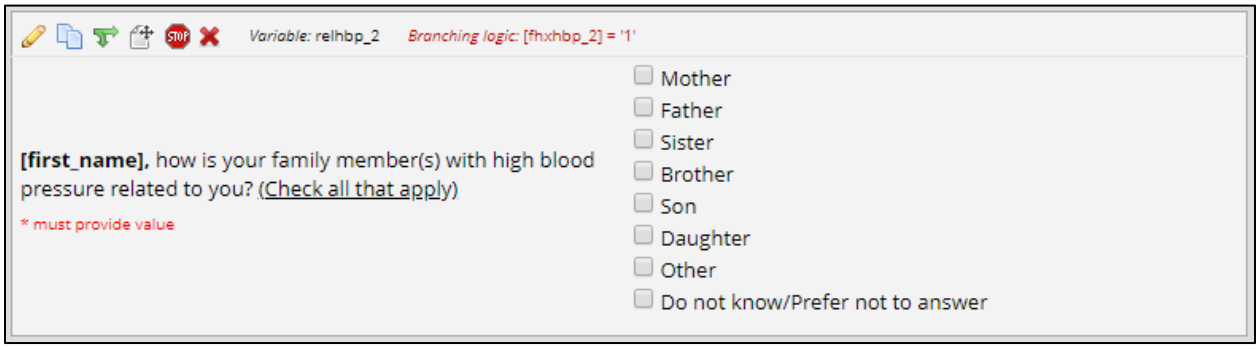


Figure 5. Family History – Converted from qualitative field to categorical/checkbox field

Study 2 – Comparing the activPAL software's Primary Time in Bed Algorithm against self-report and van der Berg's algorithm

Introduction

Researchers regularly use accelerometers to measure physical activity and sedentary behavior in the lab and in free-living settings (Bassett, 2012; Lee & Shiroma, 2014; Quante et al., 2015). When first used, participants removed accelerometers prior to going to bed, or when doing water-based activities (Bassett, 2012; Lee & Shiroma, 2014; Quante et al., 2015). Unfortunately, this often resulted in participants forgetting to replace the device, leading to potentially biased estimates of physical activity and sedentary behavior (Gibbs & Kline, 2018; Tudor-Locke et al., 2015). Nighttime removal also precluded researchers from capturing information about sleep, an important health behavior, thus preventing researchers from distinguishing the relationships between sleep, sedentary behavior, and physical activity with health outcomes (Meredith-Jones, Williams, Galland, Kennedy, & Taylor, 2016; Rosenberger, Buman, Haskell, Mcconnell, & Carstensen, 2016). Failing to distinguish or accurately identify these relationships decreased researchers' ability to understand the effects of 24-hour movement patterns on health (Meredith-Jones et al., 2016; Rosenberger et al., 2016). Researchers recognized these limitations and implemented 24-hour wear protocol in which participants wear devices at all times, with the exception of when doing water-based activities that might damage the device. These new protocol resulted in the need to develop accurate 24-hour measurements (Quante et al., 2015; Rosenberger et al., 2016), and to consider how to distinguish sleep-related behaviors from sedentary behaviors (Gibbs & Kline, 2018; Meredith-Jones et al., 2016).

Researchers consistently use the activPAL when implementing 24-hour wear protocol (PAL Technologies Ltd., 2010). The activPAL is well-suited for a 24-hour protocol because it is small, lightweight, and can be waterproofed and attached to the skin on the thigh (Edwardson et al., 2017). These characteristics increase the likelihood that participants will wear the activPAL continuously across several days, thus allowing researchers to capture 24-hour movement data. The activPAL's technology captures information about body posture, accurately determining sedentary time and distinguishing

between sedentary, stepping, and standing time in a variety of populations and settings (Kozey-Keadle, Libertine, Lyden, Staudenmayer, & Freedson, 2011; Lyden, Kozey Keadle, Staudenmayer, & Freedson, 2012; PAL Technologies Ltd., 2010; Steeves et al., 2015). The activPAL's ability to identify postural positions, and examine movement intensity, makes it possible to use it for distinguishing sedentary behavior from sleep-related behaviors, like time spent in bed (Gibbs & Kline, 2018; van der Berg et al., 2016).

As such, activPAL released an algorithm in 2019 for identifying primary and secondary lying time (PAL Technologies Ltd., 2019). Primary lying time represents the longest 'container' of lying down behavior throughout one day, and secondary lying time represents any other 'containers' of lying down behavior lasting at least 60 minutes (PAL Technologies Ltd., 2019). Primary and secondary lying time are context dependent; however, primary lying time can be a proxy for an individual's time spent in bed, which can encompass a variety of sleep-related behaviors (Gibbs & Kline, 2018; PAL Technologies Ltd., 2019). The activPAL's new algorithm has the potential to enhance researchers' ability for using the device to identify how 24-hour movement patterns relate to health outcomes (van der Berg et al., 2016). However, it is necessary to determine the accuracy of this algorithm prior to using the algorithm to explore additional research questions.

Previously, researchers relied on self-report to determine sleep time, based on time in bed (TIB), when using the activPAL (Devine, Hakim, & Green, 2005; Edwardson et al., 2017; Quante et al., 2015). Participants reported TIB via diaries, introducing the possibility of recall and social desirability biases, which can result in over- or under-estimating TIB, and misclassifying TIB as sedentary behavior, or vice-versa (Gibbs & Kline, 2018; Quante et al., 2015). Researchers also use fixed-time windows, which present similar errors to those of self-report (Meredith-Jones et al., 2016), or direct observation, a highly burdensome, costly, and largely unfeasible method with limited ecological validity (Dowd, Harrington, Bourke, Nelson, & Donnelly, 2012). Methods already exist for identifying TIB in wrist-, hip-, and waist-worn devices (Marino et al., 2013; Quante et al., 2015); however, we are aware of only one group attempting to identify TIB using activPAL data (van der Berg et al., 2016). van der Berg et al. developed

an algorithm for identifying TIB in activPAL data, and compared the algorithm to self-report and a fixed-time window (van der Berg et al., 2016). Their algorithm demonstrated high levels of agreement with self-report in identifying time spent awake, wake, and bed times, suggesting the algorithm was accurate for identifying TIB using activPAL data in middle- and older-aged adults (van der Berg et al., 2016). However, we are unaware of studies using van der Berg's algorithm, or of studies comparing the activPAL algorithm against self-report or van der Berg's algorithm.

Therefore, the purpose of this study was to compare activPAL algorithm-estimated values for TIB, wake time (WT), and bed time (BT) against self-reported and van der Berg algorithm-estimated values. We will also examined whether the type of day (e.g. weekday versus weekend day) affected the accuracy of the activPAL algorithm. A secondary purpose of this study was to compare the van der Berg algorithm-estimated values for TIB, WT, and BT against self-reported values for all days, weekdays, and weekends.

Methods

Participants

We used data from the Community Activity for Prevention Study (CAPs), a randomized controlled trial of the effects of community gardening on health outcomes (Litt et al., 2018). Eligible participants were 18 years and older, able to provide consent in English or Spanish, and were new to gardening or had not gardened in the past two years (Litt et al., 2018). CAPs included three waves of participants over three years (N=296). Data were collected at baseline, 6-months, and 1-year, with participants randomized to a gardening group or a wait-list control. Additional details on CAPs can be found elsewhere (Litt et al., 2018).

This study included baseline data from all three waves of CAPs. Participants were included if they wore the activPAL for at least 10 hours/day on three weekdays and one weekend day, provided simultaneous self-reported wake and bed times, and wore the device overnight. 187 participants were included in this study. The University of Colorado Boulder Institutional Review Board approved the study (Protocol 16-0644). Participants provided written, informed consent.

Measures

The activPAL is a small, lightweight, triaxial accelerometer that records movement in the vertical, anteroposterior, and mediolateral axes, and identifies postural positions (PAL Technologies Ltd., 2010). The activPAL was attached to the skin on the front of the right thigh with transparent tape, and participants were asked to wear the activPAL continuously over seven days, only removing the device during water-based activities such as swimming or bathing (Litt et al., 2018).

activPAL algorithm-estimated time in bed, wake time, and bed time

Raw activPAL .datx files were processed in the PALBatch software using the CREA – 10 hour wear protocol and auto-correcting inverted wear (PAL Technologies Ltd., 2019). We extracted the following variables from the Daily Time in Bed and Daily Summaries exports: 'TIB Start Date' (e.g. 'bed date'), 'TIB Start Time' (e.g. 'bed time'), 'TIB End Date' (e.g. 'wake date'), 'TIB End Time' (e.g. 'wake time'), and 'Primary Lying Time' (PAL Technologies Ltd., 2019). Lying time is determined by identifying non-upright events lasting longer than one hour and then expanding each event to adjacent non-upright events (thus allowing for bathroom breaks and other sleep interruptions), which results in a container of predominantly non-upright events (PAL Technologies Ltd., 2019). The longest container is flagged as 'Primary Lying Time', which we considered a proxy for TIB (PAL Technologies Ltd., 2019).

Self-reported time in bed, wake time, and bed time

Participants completed a self-report log for each day they wore the accelerometer. The log included the date worn, WT and BT (hh:mm), and overnight wear. TIB was calculated as the difference between self-reported bed and wake times.

van der Berg algorithm-estimated time in bed, wake time, and bed time

van der Berg et al.'s 'activPAL analyse' algorithm for determining TIB, WT, and BT (van der Berg et al., 2016) was applied to each participant's activPAL data using MATLAB R2018b (MathWorks. Natick, MA, USA). We extracted the following variables from the 'uitvoer' output file: 'rise', 'bed', and 'valid_min_sleep' (i.e. TIB).

Other variables

The following variables were obtained as described elsewhere (Litt et al., 2018): sex, race/ethnicity, age, marital status, education, and income. Height to the nearest 0.10 cm and weight to the nearest 0.23 kg were measured using a portable stadiometer (Seca 213 Portable Stadiometer; Seca) and digital platform scale (Seca 876 Digital Scale; Seca), respectively. Body mass index (BMI) was calculated using measured height and weight: weight (kg)/height (m^2). Waist circumference was measured to the nearest 0.10 cm. Height, weight, and waist circumference were measured twice, with the average measurement used for analyses.

Statistical analyses

Descriptive characteristics of the sample and the activPAL-estimated, van der Berg-estimated, and self-reported TIB, WT, and BT were calculated using mean and standard deviation for continuous variables and n (%) for categorical variables.

The absolute and relative differences between TIB, WT, and BT estimated from the activPAL algorithm, van der Berg algorithm, and self-report were calculated and described by range, mean and SD, median, and the interquartile range (IQR). Absolute and relative differences were calculated for all days, weekdays, and weekends. Absolute differences provide information regarding the overall difference between two methods without allowing over- and under-estimates to cancel each out (van der Berg et al., 2016; Welk et al., 2019), and relative differences provide information regarding the directionality of the difference between two methods, allowing researchers to identify over- versus under-estimation (Welk et al., 2019).

Mean absolute percent error (MAPE: ((predicted value – comparison value)/(comparison value))*100) between TIB values derived from all three methods were calculated for all days, weekdays, and weekends, as MAPE reflects the magnitude of individual level error and can be compared across studies and devices (Welk et al., 2019).

Separate repeated measures mixed-effects models were used to account for the lack of independence of measures within subjects and compared the differences in TIB, WT, and BT derived

from all three methods. Mixed-effects models also examined whether type of day (weekday versus weekend day) significantly affected the differences between methods and examined whether model fit improved by using a log-likelihood difference test. Intraclass correlation coefficients (ICCs) and root mean square error (RMSE) values were extracted from the results of the mixed-effects models (Welk et al., 2019).

Bland-Altman plots were used to determine the level of agreement between TIB values for all three methods and to visualize bias (Dixon et al., 2018; Welk et al., 2019). Based on Dixon et al.'s recommendation (Dixon et al., 2018), we used equivalence tests for evaluating equivalence for estimating TIB, WT, and BT between the three methods. We used the Two-One-Sided Tests (TOST) method (Dixon et al., 2018), and specified the equivalence region for the difference in means as ±0.5 hours (±30 minutes) based on van der Berg et al.'s study (2016). We selected a raw value, rather than proportional value, due to large variability in our data and for the ease of interpreting outcomes. All analyses were conducted in R version 3.6.1 (R Core Team, 2019), and statistical significance was set at $p<.05$.

Results

Table 1 shows demographics for the 187 participants included in this study and the 109 CAPs participants not included in this study. Our participants were 40.66 ± 12.95 years old, with 80.75% females, 83% white, and 29% Hispanic. Mean BMI was 27.63 ± 7.32 kg/m^2. Compared to other CAPs participants, we had a larger proportion of whites and non-Hispanics. Our sample also weighed less and had a lower BMI than other CAPs participants.

activPAL algorithm compared to self-report

Table 2 shows the mean TIB estimated by all three methods and the absolute and relative differences and the MAPE between all three methods for all days, weekdays, and weekends. Mean self-reported TIB was 8.20 ± 1.10 hours and mean activPAL TIB was 8.97 ± 1.86 hours. The median relative and absolute differences between activPAL and self-reported TIB for all days were 0.61 hours and 1.41 hours, respectively, and the median MAPE was 17.07% for all days. Mixed-effects models indicated that the activPAL algorithm predicted significantly more TIB than self-report for all days (b=0.79, 95% CI

[0.53, 1.05], ICC=0.19, RMSE=2.07). The activPAL overestimated TIB significantly more on weekends (*b*=1.03, 95% CI [0.66, 1.39], ICC=0.03, RMSE=2.71) than weekdays (*b*=0.68, 95% CI [0.42, 0.95], ICC=0.32, RMSE=1.73). Bland-Altman plots (Figure 5) indicated that there was greater agreement between activPAL and self-reported TIB when mean TIB was less than nine to ten hours; however, when mean TIB exceeded nine to ten hours, there was less agreement and greater bias. The confidence intervals in the Bland-Altman plots were also quite wide, particularly on weekends.

Equivalence tests indicated that activPAL was not equivalent to self-report in estimating TIB for all days (*t*(1084)=3.41, 90% CI [0.64, 0.91], *p*=1.00), weekdays (*t*(757)=1.88, 90%CI [0.52, 0.82], *p*=.97), or weekends (*t*(326)=3.07, 90% CI [0.75, 1.32], *p*=.99). Figure 6 shows equivalence plots for TIB for all days, weekdays, and weekends, indicating that activPAL overestimated TIB compared to self-report, with greater overestimation on weekends.

Table 3 shows the relative and absolute differences for WT and BT for all days, weekdays, and weekends. The median relative and absolute differences between activPAL and self-reported WT for all days were 15 minutes and 36 minutes, respectively. Mixed-effects models indicated that activPAL predicted a significantly later WT than self-report for all days (*b*=0.48, 95% CI [0.31, 0.65], ICC=0.02, RMSE=1.99), with no differences by weekdays versus weekends. Equivalence tests indicated that activPAL was not equivalent to self-report in estimating WT for all days (*t*(1091)=-0.38, 90% CI [0.36, 0.59], *p*=.35), weekdays (*t*(764)=-0.93, 90% CI [0.30, 0.55], *p*=.18), or weekends (*t*(326)=0.59, 90% CI [0.36, 0.81], *p*=.72). Figure 7 shows equivalence plots for WT for all days, weekdays, and weekends, indicating that activPAL estimated a later WT than self-report, with greater variability in the differences between activPAL and self-report on weekends.

The median relative and absolute differences between activPAL and self-reported BT for all days were -19 minutes and 63 minutes, respectively. Mixed-effects models indicated that activPAL predicted a significantly earlier BT than self-report for all days (*b*=-0.35, 95% CI [-0.57, -0.12], ICC=0.07, RMSE=2.20), with no differences by weekdays versus weekends. Equivalence tests indicated that activPAL was equivalent to self-report in estimating BT on all days (*t*(1143)=2.06, 90% CI [-0.47, -0.21],

p=.02) and weekdays (*t*(816)=2.22, 90% CI [-0.45, -0.16], *p*=.013), but was not equivalent to self-report on weekends (*t*(326)=0.43, 90% CI [-0.69, -0.17], *p*=.335). Figure 8 shows equivalence plots for BT for all days, weekdays, and weekends, indicating that activPAL estimated an earlier BT than self-report on weekends, and there was greater variability in the difference between activPAL and self-reported BT on weekends.

activPAL algorithm compared to van der Berg algorithm

Mean van der Berg-estimated TIB was 8.07 ± 1.31 hours (Table 2). The median relative and absolute differences between activPAL and van der Berg TIB for all days were 0.64 hours and 1.03 hours, respectively, and the median MAPE was 12.07% for all days. Mixed-effects models indicated that activPAL predicted significantly more TIB than the van der Berg algorithm for all days (*b*=0.88, 95% CI [0.68, 1.08], ICC=0.08, RMSE=1.89), and activPAL overestimated TIB significantly more on weekends (*b*=1.05, 95% CI [0.78, 1.31], ICC<.01, RMSE=2.36) than weekdays (*B*=0.78, 95% CI [0.55, 1.01], ICC=0.16, RMSE=1.71). Bland-Altman plots (Figure 5) indicated that activPAL and van der Berg-estimated TIB were in greater agreement when mean TIB was less than eight to nine hours; however, when mean TIB exceeded eight to nine hours, there was less agreement and greater bias. Additionally, activPAL and the van der Berg algorithm were in agreement for a large proportion of values.

Equivalence tests indicated that activPAL was not equivalent to the van der Berg algorithm in estimating TIB for all days (*t*(982)=4.91, 90% CI [0.74, 0.97], *p*=1.00), weekdays (*t*(680)=3.18, 90% CI [0.63, 0.91], *p*=.99), or weekends (*t*(301)=4.01, 90% CI [0.82, 1.27], *p*=1.00). The equivalence plots (Figure 6) show that that activPAL overestimated TIB compared to the van der Berg algorithm, with greater overestimation on weekends.

The median relative and absolute differences between activPAL and van der Berg WT for all days were 1 minute and 12 minutes, respectively (Table 3). Mixed-effects models indicated that activPAL predicted a significantly later WT than the van der Berg algorithm for all days (*b*=0.32, 95% CI [0.17, 0.47], ICC=0.00, RMSE=1.94), with no differences by weekdays versus weekends. Equivalence tests indicated that activPAL was equivalent to the van der Berg algorithm in estimating WT for all days

(t(986)=-2.69, 90% CI [0.21, 0.43], p<.01) and weekdays (t(684)=-2.67, 90% CI [0.16, 0.42], p<.01), but not for weekends (t(301)=-0.88, 90% CI [0.18, 0.60], p=.19). The equivalence plots (Figure 7) show that activPAL estimated a later WT than the van der Berg algorithm on weekends.

The median relative and absolute differences between activPAL and van der Berg-estimated BT for all days were -30 minutes and 53 minutes, respectively (Table 3). Mixed-effects models indicated that activPAL predicted a significantly earlier BT than the van der Berg algorithm for all days (b=-0.58, 95% CI [-0.76, -0.40], ICC<0.01, RMSE=2.46), with no differences by weekdays versus weekends. Equivalence tests indicated that activPAL was not equivalent to the van der Berg algorithm in estimating BT for all days (t(1115)=-0.89, 90% CI [-0.70, -0.44], p=.81), weekdays (t(798)=-0.28, 90% CI [-0.68, -0.37], p=.61), or weekends (t(316)=-1.24, 90% CI [-0.92, -0.44], p=.89). The equivalence plots (Figure 8) showed that activPAL estimated an earlier BT than the van der Berg algorithm, and there was greater variability in the difference between BT on weekends.

van der Berg algorithm versus self-report

The median relative and absolute differences between van der Berg and self-reported TIB for all days were 0.08 hours and 1.06 hours, respectively, and the median MAPE was 13.04% for all days (Table 2). Mixed-effects models indicated that the van der Berg algorithm predicted similar TIB to self-report for all days (b=-0.11, 95% CI [0.30, 0.07], ICC=0.07, RMSE=1.75), with no differences by weekdays versus weekends. Bland-Altman plots (Figure 5) indicated that there was reasonable agreement between the van der Berg algorithm and self-reported TIB.

Equivalence tests and plots (Figure 6) indicated that the van der Berg algorithm was equivalent to self-report in estimating TIB for all days (t(990)=6.11, 90% CI[-0.20, 0.015], p<.01), weekdays (t(686)=4.96, 90% CI [-0.25, 0.01], p<.01), and weekends (t(303)=3.58, 90% CI [-0.25, 0.19], p<.01).

The median relative and absolute differences between van der Berg-estimated and self-reported WT for all days were 7 minutes and 29 minutes, respectively (Table 3). Mixed-effects models indicated that the van der Berg algorithm predicted a significantly later wake time than self-report for all days (b=0.14, 95% CI [0.03, 0.24], ICC=0.02, RMSE=1.20), with no differences by weekdays versus

weekends. Equivalence tests and plots (Figure 7) indicated that the van der Berg algorithm was equivalent to self-report in estimating WT for all days (t(1001)=-8.57, 90% CI [0.07, 0.21], p<.01), weekdays (t(696)=-7.65, 90% CI [0.04, 0.21], p<.01), and weekends (t(304)=-4.04, 90% CI [0.04, 0.31], p<.01).

The median absolute and relative differences between van der Berg-estimated and self-reported BT for all days were 45 minutes and 9 minutes, respectively (Table 3). Mixed-effects models indicated that the van der Berg algorithm predicted a significantly later BT than self-report for all days (b=0.26, 95% CI [0.11, 0.41], ICC=0.03, RMSE=1.72), with no differences by weekdays versus weekends. Equivalence tests and plots (Figure 8) indicated that the van der Berg algorithm was equivalent to self-report in estimating BT for all days (t(1124)=-4.17, 90% CI [0.16, 0.35], p<.01), weekdays (t(803)=-3.79, 90% CI [0.13, 0.35], p<.01), and weekends (t(320)=-1.80, 90% CI [0.13, 0.48], p=.04).

Discussion

We compared activPAL algorithm-estimated TIB to self-report and van der Berg-estimated TIB, as well as van der Berg-estimated versus self-report TIB for all days, weekdays, and weekends. The activPAL algorithm estimated significantly more TIB and was not equivalent to self-report or the van der Berg algorithm. The activPAL algorithm was equivalent to self-report for estimating BT, except on weekends, suggesting that errors in activPAL estimations of WT account for the non-equivalence between activPAL-estimated and self-reported TIB. The activPAL algorithm was equivalent to the van der Berg algorithm in estimating WT, except on weekends, suggesting that errors in activPAL estimations of BT account for the non-equivalence between activPAL- and van der Berg-estimated TIB. We defined equivalence as ±30 minutes; however, as seen in the plots (Figures 6-8), using a less conservative value of ±60 minutes would have resulted in activPAL being equivalent to self-report and the van der Berg algorithm for all values, with the exception of TIB on weekends. Additionally, the Bland-Altman plots (Figure 5) showed that the activPAL and van der Berg algorithms were often in complete agreement in estimating TIB. These findings suggest that the activPAL algorithm likely only requires minor adjustments to improve its performance.

In contrast, the van der Berg algorithm was equivalent to self-report in estimating TIB, WT, and BT. While the van der Berg algorithm was equivalent to self-report, mixed-effects models indicated they were statistically different, which is likely due to the wide ranges for absolute and relative differences between van der Berg-estimated and self-reported values. The differences we found between the van der Berg algorithm and self-reported WT and BT were larger than those found in van der Berg's original study, in which the median absolute differences for algorithm versus self-reported WT and BT were 12 and 25 minutes, respectively (van der Berg et al., 2016); whereas, the median absolute difference in our study were 29 and 45 minutes, respectively. Additionally, the ranges in our study for median absolute differences were larger than van der Berg et al.'s ranges (van der Berg et al., 2016).

While it is challenging to identify sources of error in the activPAL algorithm due to limited information (PAL Technologies Ltd., 2019), activPAL provides multiple data visualization options. As such, we used the visualization software to identify potential sources of error within the algorithm. We found that the amount of time an individual lies down throughout the day might explain overestimations of TIB due to errors in identifying WT and BT. Figure 9 shows a common pattern we observed for when the activPAL algorithm overestimated TIB. As seen, the participant spent substantial time lying down throughout the day (indicated by the vertical bars below the horizontal bar), with only a few, short breaks from lying down. This appears to account for activPAL identifying a BT three hours earlier than self-report and van der Berg values (7:51PM versus 10:35PM and 10:30PM, respectively). The activPAL also identified a WT six hours later than self-report and van der Berg values (11:02AM versus 5:00AM and 5:05AM, respectively). This pattern may explain some of the error in the algorithm. Previous research found that, when identifying sleep onset via accelerometers, algorithms should require a shorter period of immobility in children compared to adolescents (Quante et al., 2015). As such, it is possible that the algorithm needs to allow for a longer period of immobility prior to identifying BT in adults.

The activPAL algorithm may need to require greater levels of stillness while lying down to correctly identify BT and WT, and to a avoid misclassifying other lying down behaviors, like watching television, as TIB. As seen in Figure 9, the size of the vertical bars change, with larger bars indicating a

greater level of stillness. The largest vertical bars, indicative of lying down with a high level of stillness, began around 11PM and ended around 5AM, times corresponding with self-reported and van der Berg-estimated BT and WT. This represents a common challenge when using accelerometers to identify sleep-related behaviors (Gibbs & Kline, 2018), with Quante et al. acknowledging the challenge of distinguishing sedentary behaviors surrounding sleep from sleep itself (Quante et al., 2015). While it is difficult to distinguish sedentary behaviors from sleep-related behaviors, Figure 9 suggests that the activPAL can likely achieve this by establishing rules that combine information about body posture, an individual's stillness, and the length of time lying down or being still to correctly distinguish sleep-related behaviors from sedentary behaviors.

Another potential source of error in the activPAL algorithm related to wakefulness after sleep onset (WASO), which occurs when an individual spends time awake in bed after initially falling asleep, but before their final awakening (Gibbs & Kline, 2018). Similar to other devices (Quante et al., 2015), the presence of WASO decreased the activPAL's ability to accurately identify WT, resulting in sometimes underestimating TIB. As shown in Figure 10, the data suggest that WASO started around 2:15AM and ended around 3:30AM, causing the activPAL to identify a WT that was seven hours earlier than self-report or van der Berg values (2:15AM versus 9:00AM and 9:05AM, respectively). This also resulted in identifying the subsequent nighttime periods of lying down (3:30-6:00AM and 7:00-9:00AM) as secondary lying time, which may not be an ideal approach, as these periods are likely indicative of sleep following WASO. Gibbs and Kline make several arguments in favor of classifying WASO as part of the sleep period (i.e. TIB), rather than sedentary behavior (i.e. 'secondary lying time'), when using devices to examine 24-hour movement patterns and transitions between sedentary behavior and sleep. Firstly it is normal to experience 60 minutes of WASO over a seven-hour sleep period and, secondly, the negative health effects of WASO only occur in combination with insufficient sleep, suggesting that, when sleep duration is sufficient, it may be appropriate to include WASO in the sleep period (Gibbs & Kline, 2018). Finally, while an individual is not asleep during WASO, the individual is *intending* to sleep; therefore, it is impractical from an intervention perspective to classify WASO as sedentary behavior, because

researchers would not target WASO to decrease sedentary behavior (Gibbs & Kline, 2018). As such, in the context of examining 24-hour movement patterns, it may be appropriate for activPAL to consider classifying WASO as part of TIB, rather than secondary lying time. This suggests that the activPAL algorithm may need to adjust its rules by allowing for WASO, which, in this example, would likely result in combining all three nighttime periods of lying down behavior into the 'primary lying time' variable (e.g. TIB).

While the activPAL algorithm encountered challenges in identifying WT and BT, it often estimated equivalent values to self-report and the van der Berg algorithm. As seen in Figure 11, the activPAL was equivalent to self-report and the van der Berg algorithm when an individual's movement pattern included minimal lying down throughout the day, a transition to extremely still lying down (e.g. BT), and a final transition to minimal lying down (e.g. WT). This clear pattern allowed for ease in identifying WT and BT. Importantly, individuals in our sample with this pattern also had a regular sleep/wake schedule, which is consistent with previous research indicating that sleep-estimation algorithms perform well in healthy sleepers, but worsen with less healthy sleepers, such as those who have greater WASO (Marino et al., 2013; Quante et al., 2015). A regular sleep/wake patterns is also a hallmark of good sleep hygiene, and may correspond with other health behaviors and 24-hour movement patterns (Quante et al., 2015). Future researchers may want to consider examining whether the regularity of an individual's sleep/wake patterns corresponds with their 24-hour movement patterns, as captured via the activPAL (Gibbs & Kline, 2018).

While identifying potential sources of error in the activPAL algorithm is helpful, users need practical information regarding how to use the existing algorithm. We submit that activPAL users can employ the algorithm, but should also continue collecting self-reported sleep data, including the time participants get into bed, begin attempting to fall asleep, stop attempting to sleep, and get out of bed (Gibbs & Kline, 2018; Quante et al., 2015). Researchers should include self-report information about sedentary behaviors preceding sleep and/or WASO to help identify individuals whose activPAL-estimates may be inaccurate. Self-report sleep logs are commonly used in conjunction with wearable devices and

provide additional information about participants' sleep, thus allowing researchers to adjust for potential errors and account for odd sleep hours, WASO, or lying down for long periods without sleeping (Quante et al., 2015). Researchers can also use electronic sleep logs, completed via mobile apps, texting, etc., which improve participant compliance and reduce burden (Quante et al., 2015).

We also recommend that researchers examine activPAL-estimated 'Primary Lying Time' values for outliers and, if found, either: 1) Remove the outliers, or 2) Manually replace the TIB 'Start' and 'End' times in the activPAL software (preferred option). These values can be replaced with self-reported data, by examining the data visually and identifying values based on patterns of lying down/stillness, or using a combination of self-report and manual scoring. Indeed, manually scoring data in conjunction with self-report improves agreement with polysomnography compared to using a completely automated approach (Quante et al., 2015). Given the high quality of the activPAL's visualization software, researchers can likely achieve accurate WT and BT estimates by visually examining the data, and referencing self-report data when needed. However, manually annotating data without using a systematic approach can introduce unwanted variability into the data, particularly when more than one person annotates the data (Quante et al., 2015). Therefore, researchers should develop a well-defined approach to adjusting data and use said approach consistently to avoid introducing variability, improve data quality, and allow replication of their approach in future studies.

Strengths and Limitations

There were many strengths to our study. We had a reasonably large sample of middle-aged adults and a large proportion of whites and Hispanics. The proportion of normal weight, overweight, and obese participations was similar to the U.S. population; thereby making our data generalizable to middle-aged whites or Hispanic in the U.S. Our participants were unaware that we were examining TIB, WT, or BT, thus reducing the likelihood that social desirability bias affected our results. Comparing self-report to the van der Berg algorithm allowed us to identify whether error occurred due to self-report biases or limitations in the activPAL algorithm, with results suggesting errors in the activPAL algorithm, rather than self-report.

There were some limitations to our study. Using self-report as the comparison introduces the potential for recall and other biases (Quante et al., 2015); however, self-report is commonly used for capturing sleep data (Devine et al., 2005; Quante et al., 2015), and our comparison to the van der Berg algorithm enhances the utility of our findings. We considered 'Primary Lying Time' as a proxy for TIB; however, the activPAL does not measure TIB per se. Rather, primary lying time is calculated based on extended periods (>60 minutes) of non-upright events (lying down) throughout the day (PAL Technologies Ltd., 2019). As such, activPAL users should note that primary lying time is not a true measure of TIB (or sleep) and that, when interpreting primary and secondary lying time, the contexts surrounding these values, such as WASO, should be considered. Researchers should also use activPAL's visualization software to understand the context surrounding these values and make adjustments to improve estimations.

Future studies should include other age groups, a more representative sample of races, and more men. The activPAL algorithm should be validated against an objective measure of sleep, ideally polysomnography (Marino et al., 2013), to identify how well activPAL-estimated TIB corresponds with actual sleeping behavior. The activPAL algorithm could also be validated against other objective measures, such as the Actiwatch (Quante et al., 2015). Researchers should also examine whether the primary and secondary lying data variables captured via the activPAL relate to sleep quantity, quality, WASO, or other sleep-related outcomes (Gibbs & Kline, 2018), as this could provide information about the practical and clinical utility of using the activPAL to measure sleep-related behaviors in free-living individuals. Finally, researchers need to validate the secondary lying time algorithm, because naps and other daytime sleep behaviors are often misidentified as sedentary behavior or non-wear time (Quante et al., 2015).

Conclusions

In conclusion, the activPAL algorithm for detecting TIB is not equivalent to self-report or the van der Berg algorithm, but is equivalent to self-report for identifying BT, except on weekends, and is equivalent to the van der Berg algorithm for identifying WT, except on weekends. Despite this lack of

equivalence, the activPAL algorithm appears to require only minimal updates to achieve equivalence with self-report and the van der Berg algorithm. ActivPAL users can start taking advantage of the new algorithm as long as they are aware of its short-comings and employ reasonable approaches to adjust for errors. While still requiring modifications, the activPAL's new TIB algorithm enhances the utility of using the activPAL for examining 24-hour movement patterns, including sleep, in free-living individuals.

Table 1. Participant demographics and descriptive statistics

Demographics	Sleep Validation Participants (N=187[a])	CAPS Participants not in Sleep Validation (N=109[b])
Age in years (Mean ± SD)[c]	40.66 ± 12.95	41.99 ± 13.70
Sex (n (%))		
Male	35 (18.72)	19 (17.43)
Female	151 (80.75)	90 (82.57)
Missing	1 (0.53)	0 (0.00)
Race (n (%))		
White	156 (83.42) [e]	78 (71.56) [e]
African American	11 (5.88)	10 (9.17)
Other	20 (10.70) [e]	19 (17.43) [e]
Missing	0 (0.00)	2 (1.83)
Ethnicity (n (%))		
Hispanic	55 (29.41) [e]	45 (41.28) [e]
Non-Hispanic	131 (70.05) [e]	62 (56.88) [e]
Missing	1 (0.53)	2 (1.83)
Anthropometrics (Mean ± SD)		
Height (inches)	65.21 ± 3.77	64.99 ± 3.68
Weight (pounds)	166.53 ± 44.21[e]	175.36 ± 45.48 [e]
BMI (kg/m^2)	27.63 ± 7.32[e]	29.21 ± 7.36 [e]
Waist Circumference (inches)[d]	35.79 ± 6.17	37.34 ± 6.45
Weight Categories (n (%))		
Normal Weight	77 (41.18)	33 (30.28)
Overweight	61 (32.62)	35 (32.11)
Obese	49 (26.20)	41 (37.61)

[a]N includes all participants who met inclusion criteria to be included in validation analyses; [b]N includes CAPS participants who were not in the sleep validation sample; [c]Missing age for 5 participants in the full sample and 4 participants in the sleep validation sample; [d]Missing waist circumference for one participant; [e]Pairwise t-tests, Wilcoxon tests, or chi-square tests were used to examine differences between CAPS study participants who were in the sleep validation sample compared to those participants who were not in the sleep validation sample, with [e] indicating statistically significant differences between the two groups.

Table 2. Comparison of time in bed values derived from the activPAL algorithm, self-report, and the van der Berg algorithm

All Days	**Measurement**	**Range**	**Mean ± SD**	**Median (Q1 – Q3)**
Time in Bed (hours)	Self-report (h)	3.73 – 11.30	8.20 ± 1.10	8.25 (7.62 – 8.89)
	activPAL algorithm (h)	3.86 – 17.21	8.97 ± 1.86	8.91 (7.94 – 9.90)
	van der Berg algorithm (h)	3.65 – 11.55	8.07 ± 1.31	8.00 (7.16 – 8.95)
Relative difference (hours)	activPAL algorithm – Self-report	-5.24 – 7.95	0.78 ± 1.80	0.61 (0.02 – 1.41)
	activPAL algorithm – van der Berg algorithm	-6.42 – 11.04	0.91 ± 1.59	0.64 (0.16 – 1.37)
	van der Berg algorithm – Self-report	-5.60 – 5.84	-0.14 ± 1.37	0.08 (-0.84 – 0.51)
Absolute difference (hours)	activPAL algorithm – Self-report	0.09 – 7.95	1.82 ± 1.42	1.41 (0.83 – 2.34)
	activPAL algorithm – van der Berg algorithm	0.00 – 11.04	1.41 ± 1.45	1.03 (0.50 – 1.97)
	van der Berg algorithm – Self-report	0.14 – 5.84	1.36 ± 1.04	1.06 (0.57 – 1.90)
Mean absolute percent error (%)	activPAL algorithm – Self-report	0.91 – 284.30	23.76 ± 24.06	17.07 (10.34 – 30.02)
	activPAL algorithm – van der Berg algorithm	-2039.82 – 833.77	15.71 ± 78.58	12.07 (5.67 – 24.02)
	van der Berg algorithm – Self-report	1.31 – 186.40	17.97 ± 18.37	13.04 (7.28 – 22.29)
Weekdays	**Measurement**	**Range**	**Mean ± SD**	**Median (Q1 – Q3)**
Time in Bed (hours)	Self-report (h)	3.73 – 11.30	8.20 ± 1.09	8.25 (7.63 – 8.89)
	activPAL algorithm (h)	3.86 – 17.21	8.97 ± 1.87	8.90 (7.94 – 9.90)
	van der Berg algorithm (h)	3.65 – 11.55	8.06 ± 1.31	8.00 (7.16 – 8.90)
Relative difference (hours)	activPAL algorithm – Self-report	-5.24 – 7.95	0.78 ± 1.80	0.61 (0.02 – 1.41)
	activPAL algorithm – van der Berg algorithm	-6.42 – 11.04	0.92 ± 1.59	0.64 (0.15 – 1.38)
	van der Berg algorithm – Self-report	-5.60 – 5.84	-0.15 ± 1.37	0.08 (-0.84 – 0.51)
Absolute difference (hours)	activPAL algorithm – Self-report	0.09 – 7.95	1.81 ± 1.42	1.41 (0.83 – 2.34)
	activPAL algorithm – van der Berg algorithm	0.00 – 11.04	1.40 ± 1.44	1.03 (0.50 – 1.97)
	van der Berg algorithm – Self-report	0.14 – 5.84	1.35 ± 1.04	1.06 (0.57 – 1.87)
Mean absolute percent error (%)	activPAL algorithm – Self-report	0.91 – 240.51	23.65 ± 22.78	17.45 (10.36 – 29.88)
	activPAL algorithm – van der Berg algorithm	-2039.82 – 833.77	14.72 ± 93.13	12.10 (5.69 – 24.49)
	van der Berg algorithm – Self-report	1.40 – 186.40	18.04 ± 18.33	13.04 (7.36 – 22.32)
Weekends	**Measurement**	**Range**	**Mean ± SD**	**Median (Q1 – Q3)**
Time in Bed (hours)	Self-report (h)	3.73 – 11.30	8.19 ± 1.13	8.25 (7.61 – 8.89)
	activPAL algorithm (h)	3.86 – 17.21	8.96 ± 1.85	8.92 (7.88 – 9.90)
	van der Berg algorithm (h)	4.47 – 11.55	8.09 ± 1.31	8.00 (7.16 – 9.00)
Relative difference (hours)	activPAL algorithm – Self-report	-5.24 – 7.95	0.79 ± 1.78	0.65 (0.02 – 1.41)

	activPAL algorithm – van der Berg algorithm	-6.42 – 11.04	0.89 ± 1.61	0.64 (0.16 – 1.37)
	van der Berg algorithm – Self-report	-4.67 – 5.84	-0.11 ± 1.37	0.08 (-0.82 – 0.51)
Absolute difference (hours)	activPAL algorithm – Self-report	0.09 – 7.95	1.83 ± 1.43	1.41 (0.85 – 2.34)
	activPAL algorithm – van der Berg algorithm	0.00 – 11.04	1.42 ± 1.48	1.03 (0.50 – 1.94)
	van der Berg algorithm – Self-report	0.14 – 5.84	1.36 ± 1.04	1.06 (0.57 – 1.91)
Mean absolute percent error (%)	activPAL algorithm – Self-report	0.96 – 284.30	24.02 ± 27.01	16.52 (10.16 – 30.06)
	activPAL algorithm – van der Berg algorithm	0.02 – 183.67	17.96 ± 21.05	12.00 (5.59 – 22.86)
	van der Berg algorithm – Self-report	1.31 – 164.80	17.82 ± 18.49	13.12 (6.83 – 22.02)

Table 3. Absolute differences in wake and bed times derived from activPAL algorithm, self-report, and van der Berg algorithm methods

		Range	Mean ± SD	Median (Q1 – Q3)
Wake times – All Days (hh:mm:ss)	**Relative differences**			
	activPAL algorithm – Self-report	-4:44:24 – 8:11:06	0:29:11 ± 1:14:08	0:15:40 (-0:01:51 – 0:39:35)
	activPAL algorithm – van der Berg algorithm	-3:50:29 – 7:55:26	0:18:29 ± 1:08:20	0:01:13 (0:00:00 – 0:23:40)
	van der Berg algorithm – Self-report	-3:49:12 – 3:07:22	0:07:51 ± 0:48:37	0:07:03 (-0:06:24 – 0:27:30)
	Absolute differences			
	activPAL algorithm – Self-report	0:01:47 – 8:11:06	1:00:29 ± 1:10:36	0:36:07 (0:18:33 – 1:13:19)
	activPAL algorithm – van der Berg algorithm	0:00:00 – 7:55:26	0:42:13 ± 1:09:34	0:12:47 (0:00:01 – 0:52:59)
	van der Berg algorithm – Self-report	0:01:24 – 4:11:21	0:43:45 ± 0:44:01	0:29:08 (0:14:01 – 0:56:21)
Wake times – Weekdays (hh:mm:ss)	**Relative differences**	**Range**	**Mean ± SD**	**Median (Q1 – Q3)**
	activPAL algorithm – Self-report	-4:44:24 – 8:11:06	0:28:56 ± 1:14:06	0:15:40 (-0:01:49 – 0:39:35)
	activPAL algorithm – van der Berg algorithm	-3:50:29 – 7:55:26	0:18:22 ± 1:07:38	0:00:15 (0:00:00 – 0:22:42)
	van der Berg algorithm – Self-report	-3:49:12 – 3:07:22	0:07:26 ± 0:48:45	0:06:47 (-0:06:24 – 0:27:30)
	Absolute differences			
	activPAL algorithm – Self-report	0:01:47 – 8:11:06	1:00:29 ± 1:10:44	0:35:36 (0:18:23 – 1:13:19)
	activPAL algorithm – van der Berg algorithm	0:00:00 – 7:55:26	0:41:34 ± 1:08:53	0:12:12 (0:00:01 – 0:51:12)
	van der Berg algorithm – Self-report	0:01:24 – 4:11:21	0:43:20 ± 0:43:51	0:28:55 (0:13:58 – 0:55:56)
Wake times – Weekends (hh:mm:ss)	**Relative differences**	**Range**	**Mean ± SD**	**Median (Q1 – Q3)**
	activPAL algorithm – Self-report	-4:44:24 – 8:11:06	-0:29:50 ± 1:14:21	0:15:40 (-0:01:51 – 0:40:06)
	activPAL algorithm – van der Berg algorithm	-3:50:29 – 7:55:26	18:46 ± 1:10:10	0:02:11 (0:00:00 – 0:24:00)
	van der Berg algorithm – Self-report	-3:49:12 – 3:07:22	0:08:54 ± 0:48:18	0:07:47 (-0:06:34 – 0:28:02)
	Absolute differences			
	activPAL algorithm – Self-report	0:01:47 – 8:11:06	1:00:37 ± 1:10:21	0:36:41 (0:19:41 – 1:13:19)
	activPAL algorithm – van der Berg algorithm	0:00:00 – 7:55:26	43:53 ± 1:11:24	0:13:44 (0:00:29 – 0:57:26)
	van der Berg algorithm – Self-report	0:01:24 – 4:11:21	0:44:49 ± 0:44:30	0:31:01 (0:15:23 – 0:56:58)
Bed times – All Days (hh:mm:ss)	**Relative differences**	**Range**	**Mean ± SD**	**Median (Q1 – Q3)**
	activPAL algorithm – Self-report	-6:48:32 – 4:54:18	-0:19:57 ± 1:33:00	-0:19:36 (-0:58:43 – 0:09:54)
	activPAL algorithm – van der Berg algorithm	-11:02:01 – 0:24:44	-0:36:17 ± 1:26:59	-0:30:05 (-1:04:43 - -0:02:25)
	van der Berg algorithm – Self-report	-4:31:09 – 3:26:27	0:15:27 ± 1:04:53	0:09:39 (-0:14:12 – 0:43:12)
	Absolute differences			
	activPAL algorithm – Self-report	0:04:11 – 7:34:28	1:31:54 ± 1:21:39	1:03:33 (0:40:27 – 1:57:53)
	activPAL algorithm – van der Berg algorithm	0:00:00 – 11:02:01	1:17:19 ± 1:23:02	0:53:09 (0:22:16 – 1:41:52)
	van der Berg algorithm – Self-report	0:04:12 – 4:34:41	1:04:39 ± 0:54:49	0:45:36 (0:28:28 – 1:27:13)
Bed times – Weekdays (hh:mm:ss)	**Relative differences**	**Range**	**Mean ± SD**	**Median (Q1 – Q3)**
	activPAL algorithm – Self-report	-6:48:32 – 4:54:18	-0:20:09 ± 1:33:57	-0:20:22 (-0:58:43 – 0:09:54)
	activPAL algorithm – van der Berg algorithm	-11:02:01 – 4:07:28	-0:36:34 ± 1:27:05	-0:30:05 (-1:04:53 – -0:02:25)
	van der Berg algorithm – Self-report	-4:31:09 – 3:26:27	0:15:19 ± 1:05:21	0:09:39 (-0:14:22 – 0:43:12)
	Absolute differences			
	activPAL algorithm – Self-report	0:4:11 – 7:34:28	1:32:07 ± 1:22:37	1:03:33 (0:39:55 – 1:57:53)
	activPAL algorithm – van der Berg algorithm	0:04:12 – 4:34:41	1:04:39 ± 0:55:07	0:45:36 (0:28:28 – 1:27:13)
	van der Berg algorithm – Self-report	0:00:00 – 11:02:01	1:17:07 ± 1:23:09	0:53:09 (0:22:06 – 1:41:52)

Bed times – Weekends (hh:mm:ss)	**Relative differences**	**Range**	**Mean ± SD**	**Median (Q1 – Q3)**
	activPAL algorithm – Self-report	-6:48:32 – 4:54:18	-0:19:36 ± 1:30:39	-0:19:36 (-0:58:43 – 0:09:54)
	activPAL algorithm – van der Berg algorithm	-11:02:01 – 4:07:28	-0:35:35 ± 1:26:52	-0:30:05 (-1:02:38 – -0:02:52)
	van der Berg algorithm – Self-report	-4:31:09 – 3:26:27	0:15:45 ± 1:03:46	0:09:39 (-0:13:43 – 0:41:33)
	Absolute differences			
	activPAL algorithm – Self-report	0:04:11 – 7:34:28	1:31:20 ± 1:19:14	1:03:35 (0:41:22 – 1:57:53)
	activPAL algorithm – van der Berg algorithm	0:00:00 – 11:02:01	1:17:48 ± 1:22:50	0:53:18 (0:23:23 – 1:45:58)
	van der Berg algorithm – Self-report	0:04:12 – 4:34:41	1:04:06 ± 0:54:06	0:46:29 (0:28:28 – 1:27:13)

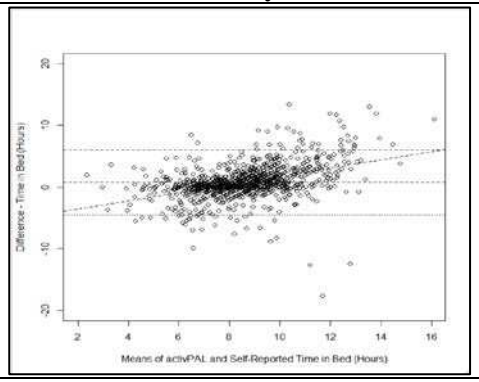
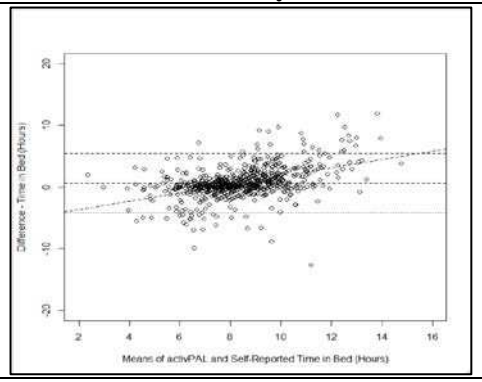
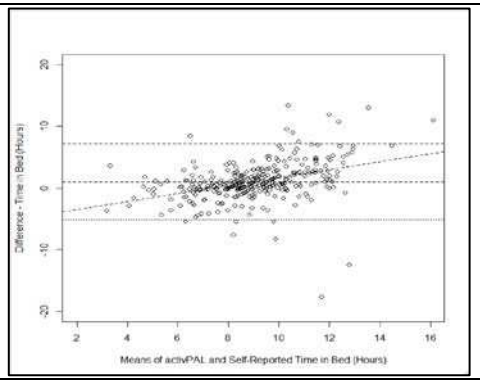
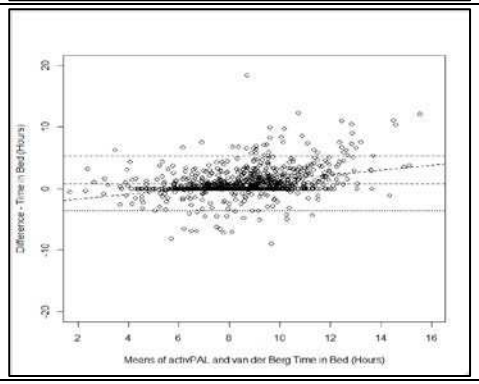
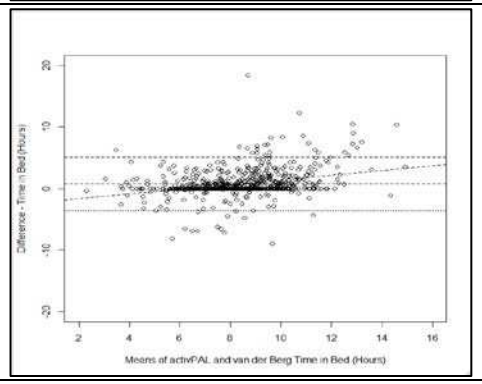
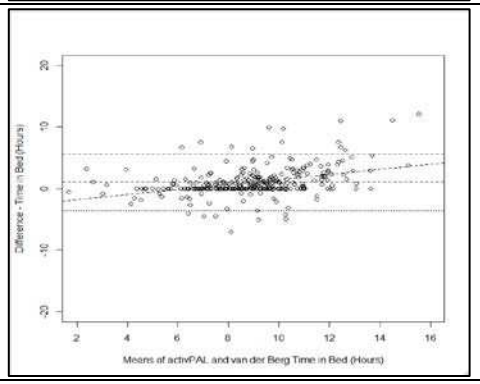
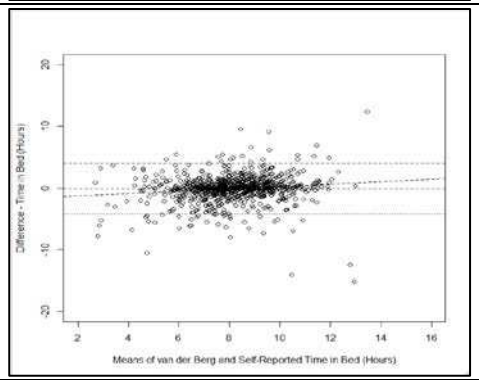
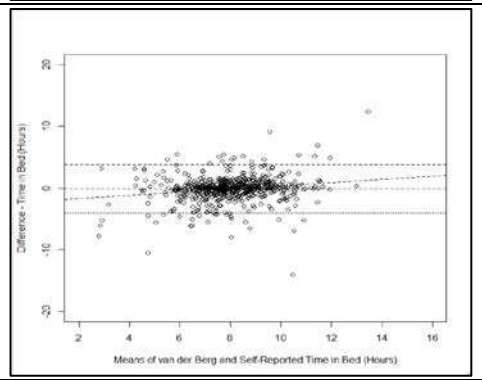
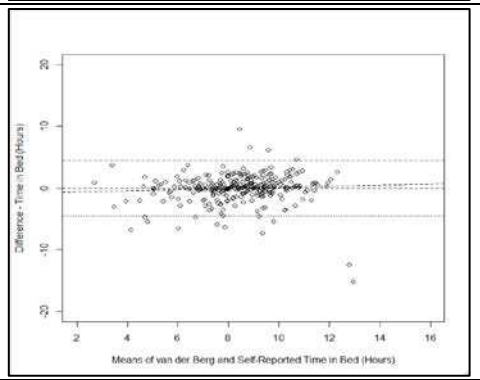
	All Days	Weekdays	Weekends
activPAL algorithm – Self-report			
activPAL algorithm – van der Berg algorithm			
van der Berg algorithm – Self-report			

Figure 6. Bland-Altman plots for time in bed for all days, weekdays, and weekends

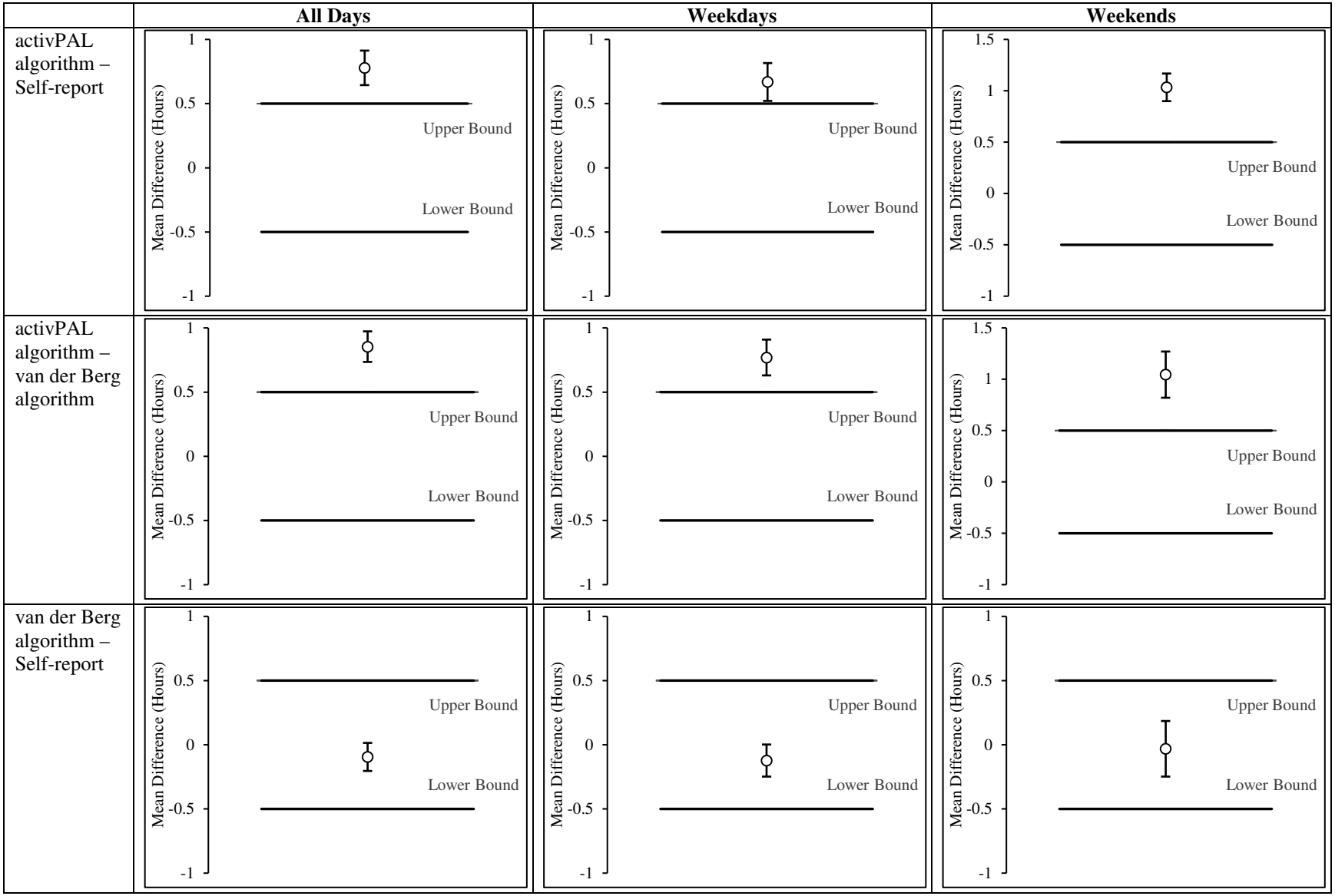


Figure 7. Equivalence plots for time in bed for all days, weekdays, and weekends

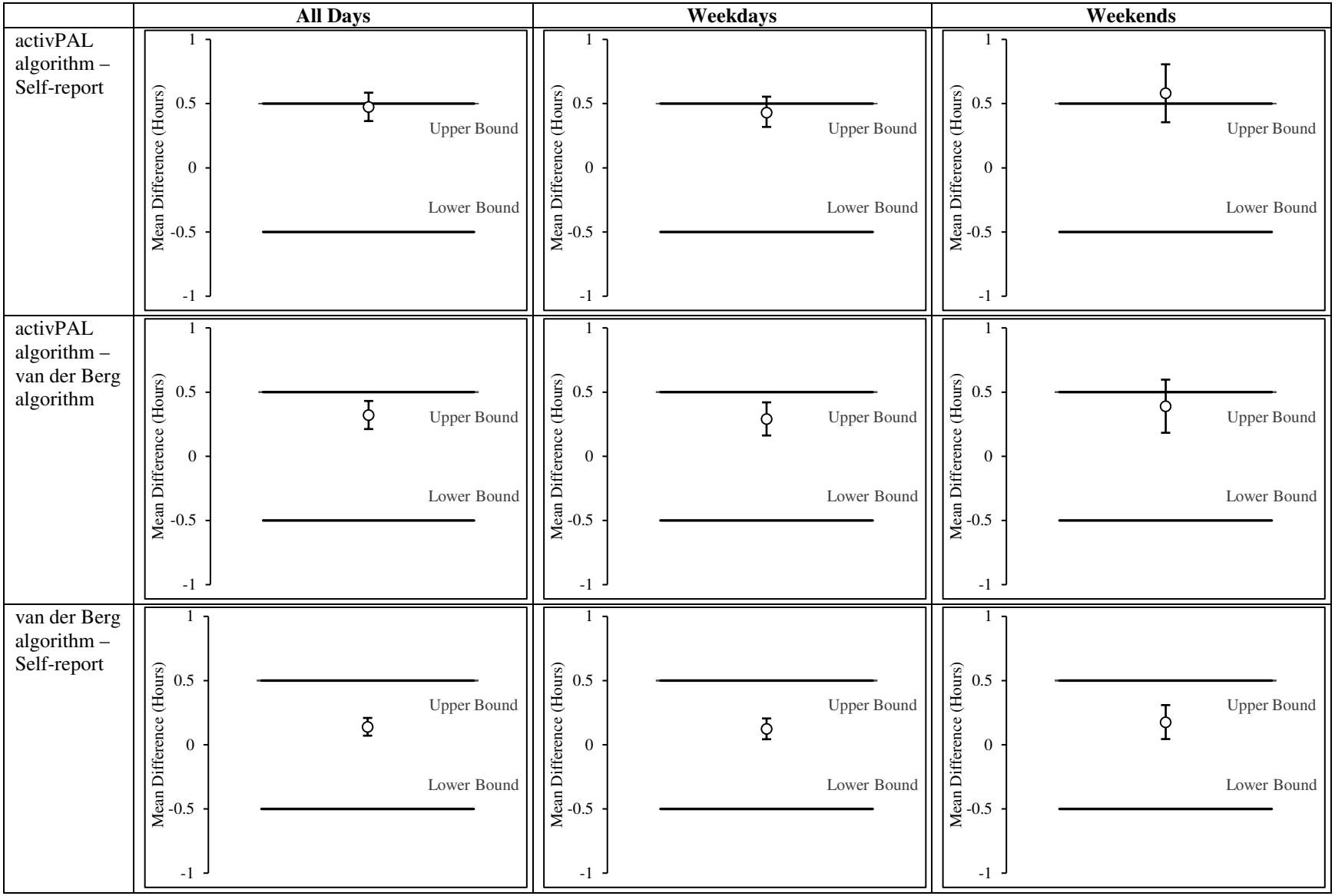


Figure 8. Equivalence plots for wake times for all days, weekdays, and weekends

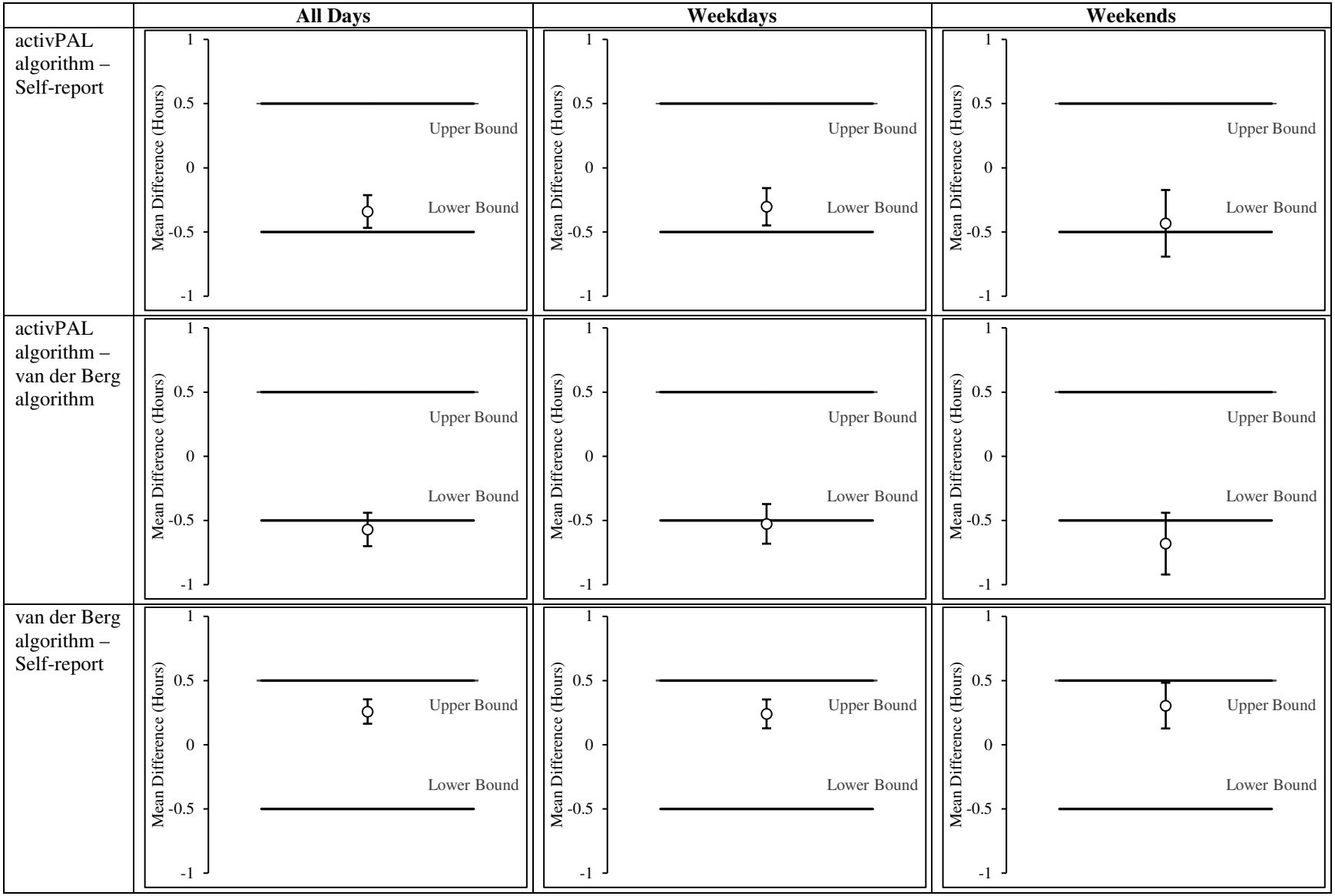
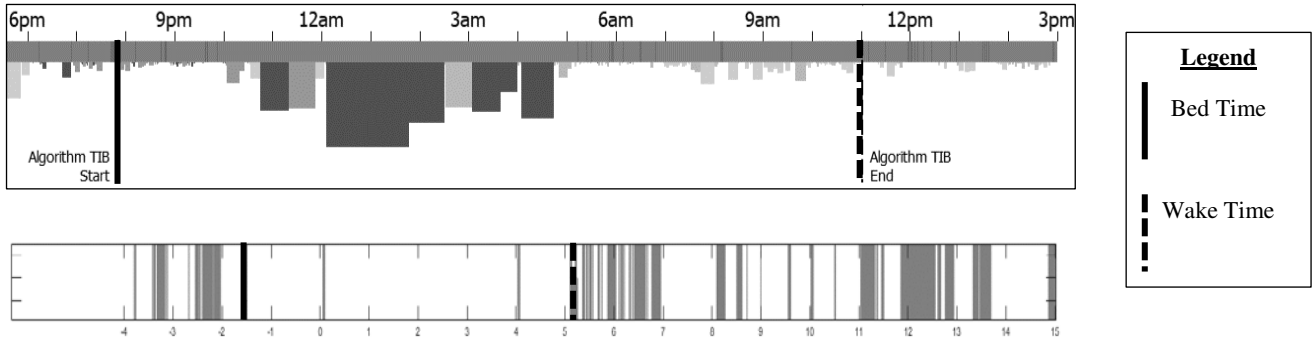


Figure 9. Equivalence plots for bed times for all days, weekdays, and weekends

a. activPAL figure of algorithm results[d]

b. MATLAB figure of van der Berg algorithm results

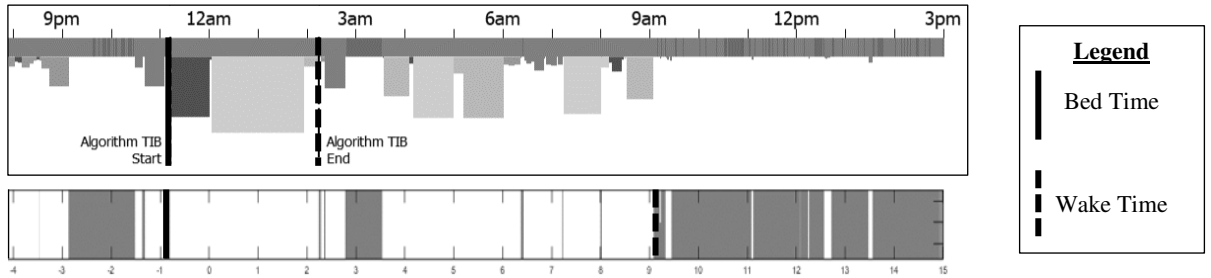


[a]activPAL bed time: 7:51PM, wake time: 11:02AM; [b]van der Berg bed time: 10:30PM, wake time: 5:05AM; [c]Self-reported bed time: 10:35PM, wake time: 5:00AM; [d]Larger vertical bars indicate a greater level of stillness. Different shades of gray represent whether the individual was lying on their back, front, left side, or right side.

Figure 10. activPAL[a] overestimating time in bed compared to van der Berg algorithm[b] and self-report[c]

a. activPAL figure of algorithm results[d]

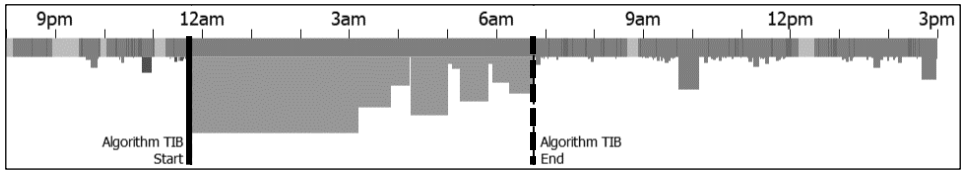
b. MATLAB figure of van der Berg algorithm results



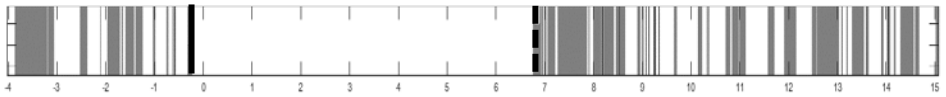
[a]activPAL bed time: 11:12PM, wake time: 2:15AM; [b]van der Berg bed time: 11:11PM, wake time: 9:05AM; [c]Self-reported bed time: 11:00PM, wake time: 9:00AM; [d]Larger vertical bars indicate a greater level of stillness. Different shades of gray represent whether the individual was lying on their back, front, left side, or right side.

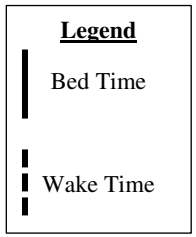
Figure 11. activPAL[a] underestimating time in bed compared to van der Berg algorithm[b] and self-report[c]

a. activPAL figure of algorithm results[d]



b. MATLAB figure of van der Berg algorithm results





[a]activPAL bed time: 11:46PM, wake time: 6:45AM; [b]van der Berg bed time: 11:46PM, wake time: 6:45AM; [c]Self-reported bed time: 11:35PM, wake time: 6:45AM; [d]Larger vertical bars indicate a greater level of stillness. Different shades of gray represent whether the individual was lying on their back, front, left side, or right side.

Figure 12. activPAL[a] estimating same bed and wake times as van der Berg algorithm[b] and self-report[c]

CHAPTER 4 – STATISTICS AND MATH

Data scientists must be capable of identifying the appropriate statistical methods to use based on the characteristics of the specific study design and sample in question, as well as employing said methods to understand study outcomes. Substantive expertise in a particular area, such as psychosocial determinants of health behaviors and health outcomes, should be used to inform which variables are included in a given analysis, how to examine the effects of said variables on study outcomes, and how to interpret outcomes. One example of this is deciding whether to control for the effects of unmodifiable determinants (i.e. sex) or to examine the potential moderating effects of unmodifiable determinants on study outcomes. These decisions require a consideration of the theoretical underpinnings of a given study's research questions, the study design, and the study sample's characteristics. The studies in this chapter provide practical examples of how data scientists can combine statistical knowledge with substantive expertise to examine the relationships among unmodifiable and psychosocial determinants of health and health behaviors. Study 3 demonstrates the use of growth modeling for examining how unmodifiable determinants, including sex and race/ethnicity, and psychosocial determinants, including autonomous motivation, controlled motivation, and PA planning, relate to PA participation in a nationally representative sample of adolescents transitioning into early adulthood. Study 4 provides an example of using smartphone technology to capture repeated measures of psychosocial determinants of health (e.g. stress and tiredness) in real-time and in an individual's natural environment, and using appropriate statistical modeling (mixed-effects location scale models) to analyze the data captured via smartphones to examine acute stress and tiredness, and between- and within-person variability in stress and tiredness among a sample of career firefighters.

Study 3 – Motivation and Planning Effects on Physical Activity during the Adolescent-to-Adult-Transition

Introduction

Although research indicates that engaging in sufficient physical activity (PA) consistently relates to better health outcomes, very few adolescents meet PA recommendations based on accelerometer-measured PA (8%) and self-reported PA (26%) (Centers for Disease Control and Prevention, 2019a; Troiano et al., 2008). These low PA rates cause concern as lower PA corresponds with greater chronic disease risk (Kohl et al., 2012; Mozaffarian et al., 2015). Increasing PA participation among adolescents may reduce their chronic disease risk; however, this requires an understanding about which factors predict PA participation. Self-determination theory (Ryan & Deci, 2000; Teixeira et al., 2012) and social cognitive theory (Sniehotta et al., 2005) suggest that two potential predictors of PA participation include motivation and planning.

In Self-Determination Theory, researchers conceptualize motivation on a continuum from non-autonomous amotivation to completely autonomous intrinsic motivation, with four subcategories of extrinsic motivation in between (Ryan & Deci, 2000; Teixeira et al., 2012). The subcategories of extrinsic motivation vary in the extent to which they are autonomously regulated (Ryan & Deci, 2000; Teixeira et al., 2012). External and introjected regulation represent the less autonomous forms of extrinsic motivation and are often combined to represent controlled motivation (Ryan & Deci, 2000; Teixeira et al., 2012; Williams et al., 1996). Identified and integrated regulation represent more autonomous forms of extrinsic motivation (Ryan & Deci, 2000; Teixeira et al., 2012). Intrinsic motivation represents the most autonomous form of motivation (Ryan & Deci, 2000; Teixeira et al., 2012). Researchers often combine identified regulation, integrated regulation, and intrinsic motivation to represent autonomous motivation (Ryan & Deci, 2000; Teixeira et al., 2012).

Greater autonomous motivation corresponds with increased PA participation (Barbeau et al., 2009; Dishman et al., 2018; Ryan & Deci, 2000; Teixeira et al., 2012; Wilson, Rodgers, Fraser, & Murray, 2004). In contrast, greater controlled motivation corresponds with lower PA participation (Ryan

& Deci, 2000; Teixeira et al., 2012) or has no association with PA participation (Teixeira et al., 2012). Dishman et al. found that adolescents who maintained higher levels of autonomous motivation for PA showed smaller declines in PA between middle and high school (Dishman et al., 2018). Adolescents with higher autonomous motivation for PA also demonstrated larger declines in valuing PA as a means to an end (a form of controlled motivation) (Dishman et al., 2018), suggesting that autonomous motivation related to PA enjoyment may displace controlled motivation. These findings suggest that motivation may be prospectively associated with PA participation and that researchers should examine the separate effects of autonomous and controlled motivation.

Despite the importance of motivation to PA participation, substantial research indicates that individuals who report being motivated to participate in PA often fail to do so (Sniehotta et al., 2005). This incongruence may relate to whether an individual actively plans to participate in PA (K. Li et al., 2014; Sniehotta et al., 2005). Action planning refers to someone making the conscious decision to engage in a behavior, and can include making concrete plans, including when, where, and how to be active (K. Li et al., 2014; Sniehotta et al., 2005). Research indicates that action planning is associated with greater PA in a variety of settings (Cao et al., 2013; K. Li et al., 2014; Scholz et al., 2008; Sniehotta et al., 2005), and interventions have successfully improved action planning as a means to increase PA (Dombrowski & Luszczynska, 2009; Koring et al., 2012). These findings suggest that PA action planning may represent an important link between motivation and PA participation.

PA participation also decreases across the lifespan (Bauman et al., 2012). Previous studies indicate that PA declines during the adolescent-to-adult transition (Gordon-Larsen, Nelson, & Popkin, 2004; Kwan, Cairney, Faulkner, & Pullenayegum, 2012; K. Li et al., 2016), a meaningful transition period characterized by changes in other health behaviors, such as increased substance use (Kwan et al., 2012) and sedentary behavior (Gordon-Larsen et al., 2004). While these studies describe the pattern of PA during the adolescent-to-adult transition, none of them examined the effects of potential predictors of PA, like motivation, on PA during the adolescent-to-adult transition.

Cross-sectional studies indicate that time-invariant variables, such as sex and race/ethnicity, correlate with PA participation in adolescents. For example, more adolescent males than females meet PA guidelines (36.6% and 17.7%, respectively) (Kann et al., 2014; Kohl et al., 2012). Race/ethnicity also relates to PA participation and, in adolescent males, 37.5% of whites, 37.2% of African Americans and 33.9% of Hispanics meet PA guidelines (Kann et al., 2014). Among adolescent females, only 18.7% of whites, 16.0% of African Americans, and 17.4% of Hispanics meet PA guidelines. Considerable differences in PA by sex and race/ethnicity suggests the need for understanding longitudinal PA patterns by sex and race/ethnicity, which could help inform the timing and content of targeted interventions.

The objectives of this study were to examine prospective associations between the slopes for PA during the adolescent-to-adult transition with the following: 1) sex and race/ethnicity; and (2) the slopes for autonomous motivation, controlled motivation, and PA planning. We hypothesized that PA would: 1) decrease across time; (2) be higher among males than females; (3) be higher among whites than other races/ethnicities; and (4) be positively associated with higher autonomous motivation and greater PA planning; and (5) not be associated with controlled motivation.

Methods

Participants

Data for this study come from the NEXT Generation Health Study (NEXT), a nationally representative cohort study starting in the 2009-2010 school year in the United States (U.S.). School districts represented the primary sampling units (PSU) and were stratified by the nine U.S. Census division. PSUs were selected with probability proportional to total school enrollment. A total of 137 PSUs with 10th grade classes were randomly recruited and 81 schools agreed to participate. One 10th grade classroom within each school was randomly selected to participate. All students in each 10th grade classroom were invited to participate (N=3796). African American participants were oversampled to improve population estimates and ensure an adequate sample size for examining racial/ethnic differences in outcomes.

Surveys were administered annually (2009–2016), during the spring of each year, and data were collected over seven waves, beginning in the 10th grade (W1) and continuing through the fourth year post-high school (W7). A total of 2785 students agreed to participate in the study. This study uses data from Waves 2 (W2, 11th grade) through 7 (W7, four years post-high school). Wave 1 data were not used due to survey questions related to motivation being different from those at wave 2 and subsequent years. For participants less than 18 years of age, parental consent and participant assent were obtained. When participants turned 18, participant consent was obtained. The Institutional Review Board of the *Eunice Kennedy Shriver* National Institute of Child Health and Development approved this study.

Measures

Dependent variable

PA participation was assessed by asking participants to report the number of days (0-7 days) over the past seven days that they were physically active for at least 60 minutes per day (Prochaska, Sallis, & Long, 2001).

Independent variables

Time-varying covariates

The three time-varying covariates were examined using previously validated questionnaires: 1) autonomous motivation (Ryan & Connell, 1989), 2) controlled motivation (Ryan & Connell, 1989), and 3) PA planning (Luszczynska, 2006). Participants completed three questions assessing the influence of autonomous motivation on PA participation by indicating how true they felt each of the following statements were with regard to the initial statement "The amount of time I am physically active during a typical day is because": (1) "I enjoy it", (2) "It fits with how I see myself", and (3) "It is personally important to me", using a 7-point Likert scale, with responses ranging from (1) "Not at all true" to (7) "Very true" (Cronbach's alpha: 0.84-0.88) (Ryan & Connell, 1989). Items were averaged (range 0-7) to account for the presence of a small number of missing responses.

Participants completed three questions assessing the influence of controlled motivation on PA participation by indicating how true they felt each of the following statements were with regard to the

initial statement “The amount of time I am physically active during a typical day is because”: (1) “I feel guilty if I do otherwise”, (2) “My parents, other family members, or friends tell me to do it”, and (3) “I am required to do it”, using a 7-point Likert scale, with responses ranging from (1) “Not at all true” to (7) “Very true” (Cronbach’s alpha: 0.51-0.61) (Ryan & Connell, 1989). Items were averaged (range 0-7) to account for the presence of a small number of missing responses.

Participants completed three questions assessing PA planning by indicating how often over the past seven days they made plans for vigorous PA, including: (1) “I planned when to exercise”, (2) “I planned how often to exercise”, and (3) “I planned where to exercise”, using a 5-point Likert scale, with responses ranging from (1) “Not at all” to (5) “Very often” (Cronbach’s alpha: 0.93-0.96) (Luszczynska, 2006). Items were averaged (range 0 – 5) to account for the presence of a small number of missing responses.

Time-invariant covariates

Participants reported sex and race/ethnicity at baseline. Participants provided self-reported height and weight each wave, which were used to calculate body mass index (BMI) (Lipsky et al., 2019). Due to substantial missing data, BMI at W2 was examined as a time-invariant covariate in the analyses.

Statistical analyses

We used a latent growth curve modeling approach in a structural equation modeling framework (Grimm, Ram, & Estabrook, 2017) to examine the longitudinal effects of the time-invariant covariates (TICs) and time-varying covariates (TVCs) on PA participation across time, selecting the model of best fit at each step. We started with a no growth model, and then examined linear, quadratic, cubic, and piecewise growth models for the outcome variable (PA). The intercept and slope for PA were allowed to vary between persons and to covary with one another. Time scores (waves) were treated as equidistant. We examined the effects of the TICs and TVCs on the model, both in isolation and additively. TICs that failed to improve model fit were removed from the model for parsimony. We examined whether the effects of TVCs should vary across time, be fixed across time, or have a random slope. Model fit was tested using the log likelihood difference test (LL Diff Test), root mean square error of approximation

(RMSEA), Confirmatory Fit Index (CFI), Tucker-Lewis Index (TLI), and Bayesian Information Criterion (BIC) values compared between models to determine the model of best fit. Data were analyzed in SAS (version 9.4) and Mplus (version 8.1). Listwise deletion was applied, as this was the default in Mplus due to the complexity of the models and presence of missing data for some of the TICs and TVCs. Mplus product support's solution to account for missing data for the TICs and TVCs involved fixing coefficients at zero; however, this only allowed the use of LL Diff Tests to test the significance of coefficients, but prohibited comparing nested models to determine the model of best fit, resulting in the final decision to use list wise deletion to ensure we obtained the model of best fit, resulting in 1414 participants in the final model. Features of the complex sampling design were taken into account, including stratifying, clustering, and sampling weights. Statistical significance was $p<.05$. Data were analyzed in 2019.

Results

Participant Characteristics

Participants were 17.16 years old (standard error of the mean (SEM)=0.02), 35.9% male, 59.8% white, 17.9% African American, and 18.5% Hispanic, and mean BMI was 24.08 (SEM=0.31) at W2. Table 4 includes participants' PA participation and average autonomous motivation, controlled motivation, and PA planning at all six time points.

Growth Model Outcomes

Model fit tests for change in PA across time indicated that a piecewise model with two pieces (Piece 1: W2–W4; Piece 2: W4–W7) provided better model fit (LL=-21051.637; BIC=44214.708, RMSEA=0.016, CFI=0.994, TLI=0.992; LL Diff Test=152.006) than the linear, quadratic, cubic, and other piecewise models. Sex, race/ethnicity, and BMI significantly improved model fit and were retained in the final model. Allowing the effects of autonomous and controlled motivation to vary with time and PA planning to have a random slope provided better model fit. Therefore, PA planning was entered as a

random slope in the final model and the effects of the TICs on the random slope for the effect of PA planning on PA were also included. Table 5 includes results from the final piecewise growth model.

As shown in Figure 12, there was an overall decrease in PA across time. Additionally, at W2, males participated in greater PA than females (b=-0.786, SE=0.145, p<.001), and whites participated in greater PA than African Americans (b=-0.542, SE=0.159, p=.001) and Hispanics (b=-0.501, SE=0.237, p=.034).

None of the TICs affected the slope of change in PA from W2–W4. Having an 'other' race/ethnicity significantly affected the slope of change in PA (b=0.256, SE=0.118, p=.030) from W4–W7. None of the other TICs significantly affected the slope of change in PA from W4–W7.

As shown in Figure 13, autonomous motivation was significantly and positively associated with PA at each wave (b: 0.196-0.384; p<.001; see Table 5 for specific values). Controlled motivation was not significantly associated with PA at any wave. The effect of PA planning on PA varied significantly between individuals, with the average effect of PA planning significantly and positively affecting PA (b=0.445, SE=0.047, p<.001). Being female significantly decreased the effect of PA planning on PA (b=-0.117, SE=0.048, p=.015). No other TICs affected the relationship between PA planning and PA.

Discussion

This study contributes to the literature by examining the longitudinal relationships between autonomous motivation, controlled motivation, and PA planning on PA among a representative cohort during the adolescent-to-adult transition. We found that PA participation between the 11th grade and four years post-high school was characterized by two distinct growth phases, the first between the 11th grade and one-year post-high school, and the second between one and four years post-high school. Individual characteristics, including being female and African American or Hispanic corresponded with lower PA than being male or White, respectively. In alignment with our hypotheses, controlled motivation was not significantly associated with PA; whereas, autonomous motivation was significantly and positively associated with PA and PA planning significantly and positively predicted PA.

One of our most unique findings was that PA participation during the adolescent-to-adult transition was characterized by two distinct phases, and that, while PA decreased across time, there existed a trend for an increase in PA between one and two years post-high school. Only a few studies have examined PA during this transition, all finding that PA decreased across time (Gordon-Larsen et al., 2004; Kwan et al., 2012; K. Li et al., 2016). Gordon-Larsen et al.'s study used logistic regression, precluding their ability to examine the pattern of PA participation (Gordon-Larsen et al., 2004). Kwan et al. used mixed-effects modeling and found a linear pattern of decreased PA across time, which could be due to their data being collected biannually, rather than annually, suggesting they might have missed a trend for an increase in PA between one and two years post-high school (Kwan et al., 2012). Li et al.'s study used data from the NEXT study to examine accelerometer-measured PA from 10th grade through one year post-high school, thus missing the later increase between one and two years post-high school (K. Li et al., 2016). Interestingly, Li et al. found that being in school versus not attending school, and living on campus versus living at home was associated with an increased likelihood of engaging in PA during the first year post-high school (K. Li et al., 2016), and, although the complexity of our models precluded examining this, future studies should examine the longer term longitudinal relationships between school status and residence on PA. Our study design enabled us to capture a transient increase in PA during one-to-two years post high school, whereas previous studies may have failed to detect this transient increase due to different analytical or methodological approaches (Gordon-Larsen et al., 2004; Kwan et al., 2012; K. Li et al., 2016). Our findings are unique from these studies in suggesting that one-to-two years post-high school may represent a unique time period with regard to PA participation.

The finding that autonomous, but not controlled, motivation was significantly associated with higher PA corresponds with previous literature (Barbeau et al., 2009; Dishman et al., 2018; Teixeira et al., 2012; Wilson et al., 2004), and contributes to the existing literature by revealing that this relationship persists during the adolescent-to-adult transition. Autonomous forms of motivation, particularly intrinsic motivation, works by prompting behaviors that fulfill psychological needs, such as relatedness and competence (Barbeau et al., 2009). Characteristics of PA, such as social engagement, the need to

overcome challenges, and the desire to develop PA-specific skills, align with these psychological needs (Barbeau et al., 2009) and enhance autonomous motivation for PA (Teixeira et al., 2012). Our findings suggest that the role of autonomous motivation in increasing PA in adolescents transitioning into adulthood parallels that in other populations (Barbeau et al., 2009; Dishman et al., 2018; Ryan & Deci, 2000; Teixeira et al., 2012). However, our analyses only examined autonomous versus controlled motivation; therefore, future research should consider distinguishing among more specific regulatory styles of motivation to inform interventions (Ryan & Deci, 2000).

Our finding that PA planning was positively associated with PA participation aligns with previous literature (Cao et al., 2013; K. Li et al., 2014; Scholz et al., 2008; Sniehotta et al., 2005). This is particularly important, as previous interventions have successfully improved PA planning and, subsequently, PA (Dombrowski & Luszczynska, 2009; Koring et al., 2012). However, our finding that the effects of PA planning on PA varied significantly between individuals suggests that its effects during the adolescent-to-adult transition may be more nuanced than previously assumed. For example, the effects of PA planning on PA were attenuated in females in our sample, a particularly concerning finding since females already participate in less PA than males. This finding suggests that other factors (e.g., autonomous motivation) may be more important drivers of PA in females. Additional research identifying which characteristics distinguish between individuals for whom PA planning does/does not affect their PA is warranted. Successfully identifying such characteristics could inform research regarding which individuals would benefit from interventions focused on PA planning versus individuals who might benefit from interventions focusing on other predictors of PA.

Our findings related to sex and race/ethnicity correspond with the preponderance of previous literature, all of which indicates that females, including adolescents and young adults, participate in less activity than males (Kann et al., 2014), and white adolescents participate in more PA than either African Americans or Hispanics (Kann et al., 2014). These findings suggest the need to tailor interventions based on sex and race/ethnicity to increase PA.

Limitations

There are limitations to this study. Due to intermittent missing data for BMI across the time points, we included BMI at wave 2 as a TIC rather than a TVC in the model, limiting our ability to assess the longitudinal relationship between changes in BMI and PA participation. However, that BMI did not significantly affect PA participation at W2 suggests that this likely did not affect the study outcomes. We relied on self-reported measures of PA, autonomous and controlled motivation, and PA planning, increasing risk for self-report biases. Research indicates that individuals over-report PA participation and, as such, readers should interpret the average levels of PA reported in this study with caution. Finally, we were unable to examine the relationship between distinct types of motivation and PA, limiting the specificity of our findings for informing future interventions.

Conclusion

Overall, we found that PA participation during the adolescent-to-adult transition was characterized by two distinct phases, with a transient increase in PA between one and two years post-high school. Females and African Americans and Hispanics participated in significantly less PA at baseline than males and Whites, respectively. Autonomous motivation and PA planning were significantly and positively associated with PA; whereas, controlled motivation was not associated PA. The effect of PA planning on PA varied significantly between individuals. Our findings suggest that future interventions may require tailoring based on sex and race/ethnicity and may benefit from focusing on PA planning and/or autonomous motivation to increase PA during the adolescent-to-adult transition.

Table 4. Participant descriptive statistics for model variables

Study Variables (Mean ± SEM)[a]	Wave 2[b]	Wave 3[b]	Wave 4[b]	Wave 5[b]	Wave 6[b]	Wave 7[b]
Physical Activity Participation[c]	3.95 ± 4.84	3.91 ± 4.94	3.46 ± 4.93	3.35 ± 4.98	3.09 ± 4.82	3.03 ± 4.90
Autonomous Motivation[d]	4.59 ± 3.05	4.65 ± 2.97	4.50 ± 3.58	4.47 ± 3.66	4.26 ± 3.57	4.18 ± 3.58
Controlled Motivation[e]	2.66 ± 2.11	2.77 ± 2.23	2.53 ± 1.95	2.38 ± 1.65	2.35 ± 1.72	2.60 ± 1.86
Physical Activity Planning[f]	2.98 ± 1.92	3.14 ± 1.96	3.17 ± 1.93	3.03 ± 2.14	2.89 ± 2.06	2.69 ± 2.04

[a]All values were stratified by U.S. census division, clustered by primary sampling unit, and weighted based on oversampling African Americans. SEM = Standard Error of the Mean.
[b]Wave 2 occurred during the 11th grade. Wave 3 occurred during the 12th grade; and Waves 4-7 occurred during one to four years post-high school, respectively.
[c]Average days per week participant was physically active for at least 60 minutes per day.
[d]Sample average of the three questions assessing autonomous motivation for physical activity.
[e]Sample average of the three questions assessing controlled motivation for physical activity.
[f]Sample average of the three questions assessing physical activity planning.

Table 5. Growth model examining physical activity participation from 11th grade through the four years post-high school

	Estimate	*SE*
Intercept	**4.661**	**0.160*****
Female effect on intercept (ref: Male)	**-0.786**	**0.145*****
Race/Ethnicity effect on intercept (ref: White)		
African American	**-0.542**	**0.159****
Hispanic	**-0.501**	**0.237***
Other	-0.371	0.322
BMI[a] effect on intercept	-0.005	0.018
Piece 1 Time (linear slope): Wave 2 – Wave 4	**-0.285**	**0.072*****
Female effect on piece 1 (ref: Male)	0.081	0.094
Race/Ethnicity effect on piece 1 (ref: White)		
African American	-0.022	0.101
Hispanic	0.031	0.119
Other	-0.190	0.197
BMI[a] effect on piece 1	0.012	0.012
Piece 2 Time (linear slope): Wave 4 – Wave 7	**-0.125**	**0.062***
Female effect on piece 2 (ref: Male)	-0.082	0.061
Race/Ethnicity effect on piece 2 (ref: White)		
African American	0.016	0.071
Hispanic	-0.008	0.098
Other	**0.256**	**0.118***
BMI[a] effect on piece 2	-0.007	0.007
Random Slope for Physical Activity Planning and Physical Activity	**0.445**	**0.047*****
Effects of the Time Invariant Covariates on the Random Slope for Physical Activity Planning on Physical Activity		
Female effect on PA planning (ref: Male)	**-0.117**	**0.048***
Race/Ethnicity effect on PA planning (ref: White)		
African American	-0.072	0.050
Hispanic	0.008	0.061
Other	-0.056	0.103
BMI[a] effect on PA planning	-0.001	0.005
Associations of Physical Activity with Autonomous and Controlled Motivation at Each Wave		
Wave 2 Physical Activity		
Autonomous Motivation	**0.384**	**0.048*****
Controlled Motivation	0.002	0.050
Wave 3 Physical Activity		
Autonomous Motivation	**0.338**	**0.059*****
Controlled Motivation	0.110	0.077
Wave 4 Physical Activity		
Autonomous Motivation	**0.292**	**0.048*****
Controlled Motivation	0.055	0.053
Wave 5 Physical Activity		
Autonomous Motivation	**0.236**	**0.040*****
Controlled Motivation	0.094	0.070
Wave 6 Physical Activity		
Autonomous Motivation	**0.282**	**0.044*****
Controlled Motivation	0.085	0.046
Wave 7 Physical Activity		
Autonomous Motivation	**0.196**	**0.046*****
Controlled Motivation	0.073	0.048

Boldface indicates statistical significance (*p<0.05, **p<.01, ***p<0.001). [a]BMI = Body Mass Index. BMI is based on self-reported BMI at wave 2 and was centered at the sample mean.

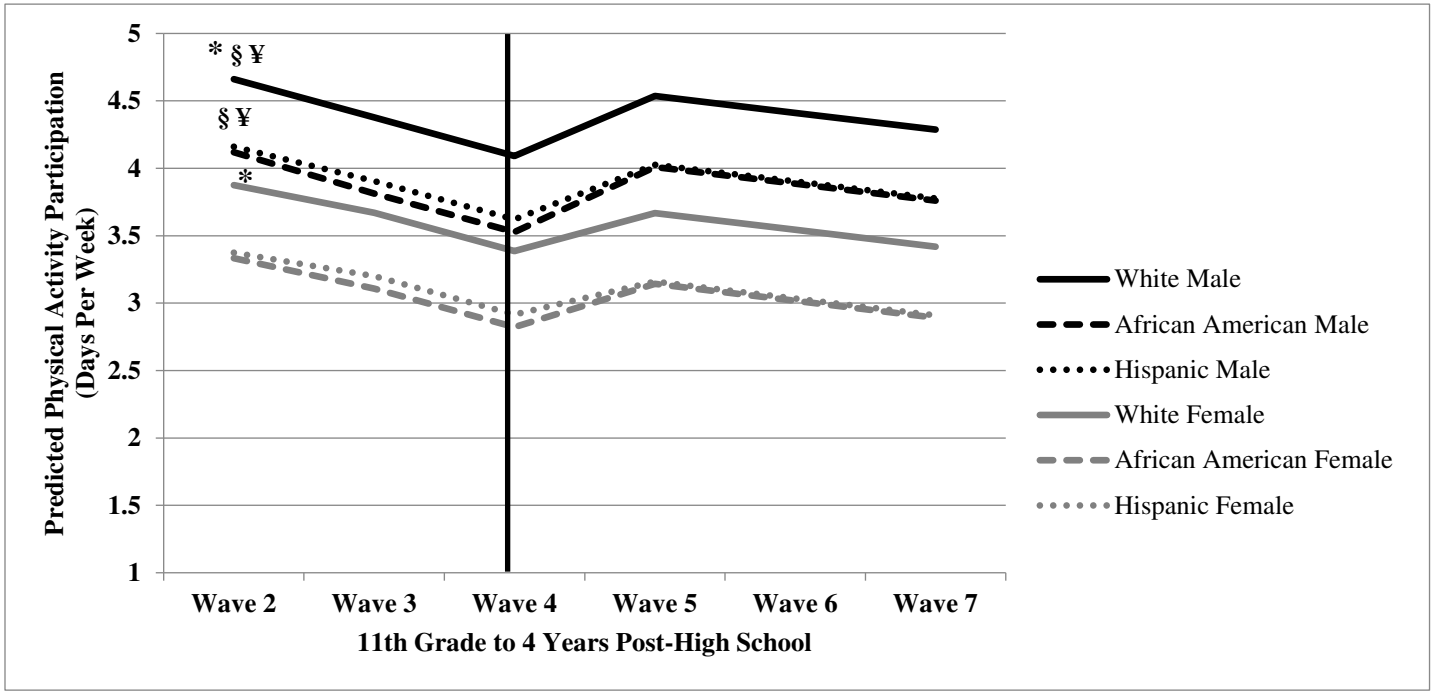


Figure 13. Sex and race differences in longitudinal participation in physical activity

*Being female predicted participating in significantly less physical activity at Time 0 (11th Grade) compared to being male, *b*=-0.786, *p*<.001. §Being African American predicted participating in significantly less physical activity at Time 0 (11th Grade) compared to being White, *b*=-0.542, *p*=.001. ¥ Being Hispanic predicted participating in significantly less physical activity at Time 0 (11th Grade) compared to being White, *b*=-0.501, *p*=.034. The solid vertical line separates Piece 1 (W2–W4) and Piece 2 (W4–W7) of the piecewise growth model.

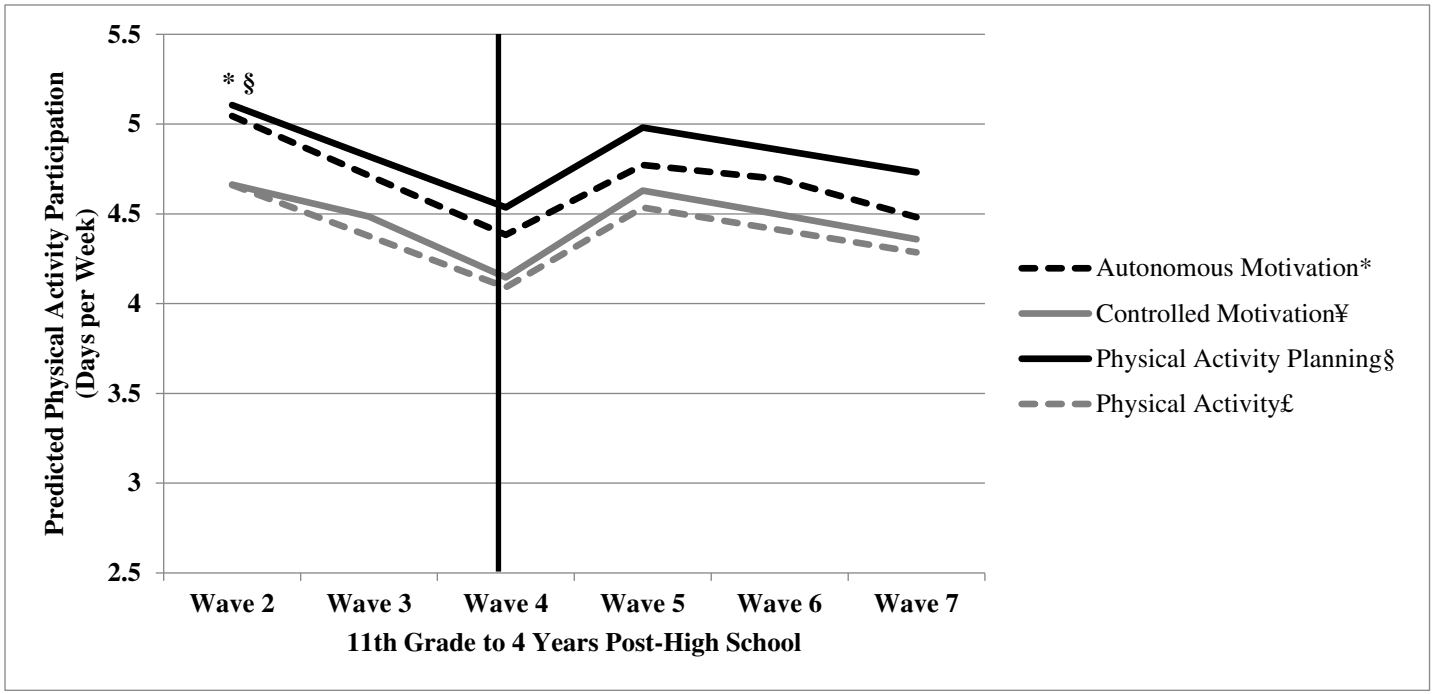


Figure 14. Effects of autonomous motivation, controlled motivation, and physical activity planning on longitudinal participation in physical activity

*Autonomous motivation was significantly and positively associated with physical activity at all times, b=0.196-0.384, p<.001. §Physical activity planning had a random slope and significantly and positively predicted with physical activity participation, b=0.444, p<.001. ¥Controlled motivation was not significantly associated with physical activity participation at any time point. £Physical activity without controlling for autonomous motivation, controlled motivation, or physical activity planning. The solid vertical line separates Piece 1 (W2–W4) and Piece 2 (W4–W7) of the piecewise growth model.

Study 4 – Using ecological momentary assessment to examine the effects of duty status on acute stress and tiredness in firefighters: A pilot study

Introduction

On-duty firefighters experience a variety of psychological stressors, such as rescuing or losing victims and low situational control (Guidotti, 1992; Soteriades, Smith, Tsismenakis, Baur, & Kales, 2011), which increase the risk of post-traumatic stress disorder and other stress-related symptoms (Dean, Gow, & Shakespeare-Finch, 2003). Psychological stress also significantly affects physiological reactivity to and recovery from stressful events, causing adverse changes in heart rate, systolic blood pressure, and cortisol levels (Dean et al., 2003; Guidotti, 1992; Roy, Steptoe, & Kirschbaum, 1998), which put firefighters at a higher-than-normal risk for cardiovascular disease (CVD) (Soteriades et al., 2011). In fact, CVD accounts for 45% of on-duty deaths in firefighters (Soteriades et al., 2011).

Sleep disturbances may also play a role in firefighters' increased CVD risk, as research consistently indicates that insufficient sleep correlates with increased risk for CVD and metabolic disease (Kashani et al., 2012; Wolk et al., 2005) and predicts increased risk for coronary events and hypertension (Kashani et al., 2012; Wolk et al., 2005). Unfortunately, firefighters' shift work and job-related stressors increase their risk for insufficient sleep (Akerstedt et al., 2002; Akerstedt et al., 2007; Akerstedt et al., 2012; Kashani et al., 2012). The independent effects of sleep and stress on CVD, as well as the relationship between sleep and stress, suggests that both variables may represent important predictors of CVD risk and other health outcomes in firefighters.

Previous investigations used retrospective surveys to assess stress and tiredness in firefighters (Chamberlin & Green, 2010; Guidotti, 1992; Soteriades et al., 2011), which fail to capture acute stress or tiredness levels or dynamic changes in stress and tiredness. In contrast, ecological momentary assessment (EMA) allows researchers to collect repeated, real-time measurements of variables (e.g., experiences, feelings) within an individual's real environment (Shiffman, Stone, & Hufford, 2008; J. M. Smyth & Stone, 2003), and smartphone applications (Houghton, 2018) allow researchers to implement EMA on a large scale and in difficult to access populations, like firefighters. Researchers have successfully used

EMA to assess acute psychological stress (J. Smyth et al., 1998; J. M. Smyth & Stone, 2003; Yang, Ryu, & Choi, 2019) and tiredness (Buysse et al., 2007; Hacker & Ferrans, 2007). However, few studies have employed EMA to examine psychological stress in firefighters (Gomes et al., 2013; Kaikkonen, Lindholm, & Lusa, 2017; Rodrigues, Paiva, Dias, & Cunha, 2018), with no studies (to our knowledge) assessing acute tiredness in firefighters. EMA studies in firefighters also typically occur over a single, 24-hour shift period, failing to capture information about firefighters when they are off-duty (Gomes et al., 2013; Kaikkonen et al., 2017; Robinson, Leach, Owen-Lynch, & Sunram-Lea, 2013; Rodrigues, Paiva, et al., 2018; Schwerdtfeger & Dick, 2019). As such, there is a need for researchers to capture acute stress and tiredness data in firefighters when they are on- and off-duty and across multiple shift periods.

Therefore, the purposes of this study were to: 1) test the feasibility of capturing acute psychological stress and tiredness in firefighters using a smartphone-based EMA approach; and 2) characterize firefighters' acute stress and tiredness by duty status. We hypothesized that: 1) capturing acute psychological stress and tiredness measures in firefighters would be feasible using smartphone-based EMA, and 2) being on-duty would significantly increase acute stress and tiredness levels and variability in firefighters.

Methods

Participants

A convenience sample of participants were recruited via email from fire departments participating in Colorado State University's Firefighter Testing Program. Participants were full-time, career firefighters on active duty who worked a shift-schedule, including the Kelly schedule (two repetitions of 24 hours on/24 hours off, followed by 24 hours on/96 hours off) or the 48/96 schedule (48 hours on/96 hours off). Firefighters were excluded if they were taking medication for or attending psychological counseling for depression or anxiety. Out of the 55 firefighters who expressed interest in participating, 39 firefighters were included in the final analyses. Participants were compensated up to $34 for participating. This study was approved by the Colorado State University Institutional Review Board.

Procedures

Interested participants provided informed consent via an electronic survey completed using the Research Electronic Data Capture (REDCap) platform (P. A. Harris et al., 2009). Upon providing consent, participants completed an electronic screening survey and a demographics survey.

Eligible participants provided their shift schedules for researchers to schedule three, eight-day EMA assessment periods. Each assessment period included at least three on-duty days and no vacation days, and there was at least a two week break between each assessment period. Participants used their personal smartphones to report their nighttime sleep, recent sleep, current stress, and current tiredness levels using the Ilumivu mEMA smartphone application (Houghton, 2018). Participants were prompted to complete seven EMA surveys between 8AM and 9PM each day. The first survey was scheduled at 8AM and the subsequent six surveys were randomly sent out every two hours between 9AM and 9PM. Each survey required 2-3 minutes to complete. After completing the three EMA periods, participants completed a feasibility survey in REDCap (P. A. Harris et al., 2009) .

Measures

The demographics survey included firefighters' date of birth, biological sex, race/ethnicity, marital status, education, shift schedule type, and years in the fire service.

Researchers developed a 13-item feasibility survey consisting of 10 questions on a 0 to 100 visual analog scale (VAS) assessing participants' perceptions of the feasibility of completing the daily EMA surveys, such as whether the surveys interfered with their work or home duties, the ease of and time required to complete surveys, and whether the surveys allowed participants to provide adequate information about their sleep, stress, and tiredness. The 10 VAS questions demonstrated high internal consistency (Cronbach's alpha=0.90 [95% CI: 0.84, 0.94]). We calculated an average feasibility score using participants' responses for the 10 VAS questions. When necessary, questions were reverse scored, such that the average score ranged from 0 to 100, with 0 representing low feasibility and 100 representing high feasibility.

The EMA prompt at 8AM asked about participants' current duty status and included a series of questions about their nighttime sleep, including the number of call and non-call related sleep disruptions (0 to 7 or more), total number of sleep bouts, and how many minutes they slept the previous night. They answered a single-item VAS measure about stress: "How stressed are you right now on a scale of 0-100, with 0 being "Not at all stressed" and 100 being "The most stressed I've ever been in my life?", and a single-item VAS measure about tiredness: "How tired are you right now on a scale of 0-100, with 0 being "Not at all tired" and 100 being "The most tired I've ever been in my life?". Single-items were used to assess stress and tiredness due to concerns over respondent burden in EMA studies related to the frequent repeated measures (Collins & Muraven, 2007). Previous researchers found that single-item stress and tiredness measures demonstrate acceptable reliability and validity and perform comparably to longer assessments (Littman, White, Satia, Bowen, & Kristal, 2006; van Hooff, Geurts, Kompier, & Taris, 2007). The six EMA prompts participants received between 9AM and 9PM asked about current duty status, any sleep bouts since their previous assessment, and the single-item stress and tiredness measures. Participants received 168 EMA survey prompts over the three, eight-day assessment periods.

Statistical analyses

Descriptive statistics were calculated using range, mean and standard deviation for continuous variables, and n and percent for categorical variables.

We calculated participants' EMA survey completion rates by examining the proportion of assigned EMA surveys completed in total, by duty status and by time of day the survey was assigned. Logistic regression analyses predicting the odds of EMA survey completion as a function duty status during the daytime and the time of day the survey was assigned.

We used mixed-effects location scale models (MELSM), estimated using maximum-likelihood methods (Hedeker, Mermelstein, & Demirtas, 2008), to examine the effects of duty status on acute stress and tiredness. MELSMs function as an extension of random-intercept models by including log-linear sub-models for within-subject and between-subject variance, which allows covariates to influence within-subject and between-subject variation (Hedeker et al., 2008). MELSMs allow an examination of whether

the effects of covariates can explain some of the variation in within-subject and between-subject variation, over and above the effects of covariates on the mean response (Hedeker et al., 2008). MELSMs include random subject effects for the mean response (random location effect) and for a subject's within-subject variance (random scale effect), thus allowing for different average levels of and consistency in the outcome (Hedeker et al., 2008). MELSMs also account for correlations among random location and scale effects. We used the MIXREGLS program developed by Hedeker and Nordgren (Hedeker & Nordgren, 2013) for the MELSMs. MIXREGLS estimates the full MELSM in three sequential stages, with the stage 1 model examining between-subject variance effects, the stage 2 model examining between-subject and within-subject variance effects, and the stage 3 model (full model) examining between-subject and within-subject variance effects, the association of the random location and scale effects, and the random scale effects (for further details regarding model estimation using MIXREGLS see Hedeker and Nordgren, 2013).

Preliminary analyses indicated that a firefighter's duty status during the prior night and during the current day (the day during which they completed EMA surveys) affected acute stress and tiredness levels. As such, duty status was examined based on the firefighter's duty status the prior night and during the day, resulting in four duty status categories: 1) Off-duty prior night/Off-duty day ("off night/day"), 2) On-duty prior night/On-duty day ("on night/day"), 3) On-duty prior night/Off-duty day ("on night/off day"), and 4) Off-duty prior night/On-duty day ("off night/on day"). We also examined the effects of nighttime and daytime sleep variables, including nighttime sleep hours, total nighttime sleep disruptions (created by summing call and non-call related sleep disruptions), total nighttime sleep bouts, recent daytime sleep (a.k.a. 'taking a nap'), and length of daytime sleep on acute stress and tiredness. We examined the effects of demographic characteristics, including shift schedule type, years in the fire service, age, sex, and race/ethnicity on acute stress and tiredness. Model fit was tested at each step using log-likelihood difference tests (LL Diff Test) and values were compared between the stage 1, 2, and 3 models to determine the model of best fit. We compared the effects of different types of duty status on means, WS, and BS variance in the outcomes by changing the reference group and re-fitting the models.

We converted the log-linear values for between-subject and within-subject variance reported in the model outcomes to the original 0 – 100 VAS for the purposes of plotting the data, interpreting the data, and calculating intraclass correlation coefficients (ICC) (for further details on the conversion of log-linear values and calculations of ICCs, see Hedeker and Nordgren, 2013). ICCs were used to examine the proportion of variance due to between-subject versus within-subject effects.

Descriptive statistics of demographic characteristics, the feasibility survey, and the logistic regression analyses of EMA survey completion rates were analyzed in R (version 3.6.1) (R Core Team, 2019). The MELSMs were estimated using MIXREGLS (Hedeker & Nordgren, 2013). Statistical significance was set at $p<.05$.

Results

Participant demographics and EMA survey descriptive characteristics

Table 6 includes demographics for the study participants (n=39). The majority of participants were white (n=33, 85%) and male (n=34, 87%). Participants were 39 ± 11 years old and had served in the fire service for 13 ± 9 years. Across all EMA surveys, firefighters reported an average acute stress level of 22 ± 14 and an average acute tiredness level of 29 ± 18. Firefighters slept an average of 7 ± 1 hours per night. The total number of nighttime sleep disruptions ranged from 0 to 8, with a median and mode of 1.

Feasibility and EMA survey completion rates

Overall, firefighters reported a mean feasibility score of 73 ± 18 out of 100. Firefighters completed 61 ± 30% of all EMA surveys assigned. Logistic regression analyses revealed no significant differences in EMA survey completion rates by duty status or by time of day.

Mixed-effects location scale model - Stress

The model of best fit for stress indicated that only duty status and total nighttime sleep disruptions significantly predicted acute stress in firefighters. None of the other sleep-related variables or demographic characteristics predicted acute stress. LL Diff Tests revealed that the stage 3 model provided the model of best fit (LL Diff Test = 25318.289 – 24204.72 = 1113.569). Table 7 includes the outcomes for the stage 3 MELSM for acute stress.

As shown in Figure 14, there were significant main effects of duty status on acute stress, with firefighters reporting the lowest levels of acute stress when they were "off night/day" (β_1=16.27) and the highest levels when they were "on night/day" (β_1+β_2=24.47). There were significant differences in the effects of duty status on acute stress between all types of duty status, with the exception of "on night/day" versus "off night/on day". Total nighttime sleep disruptions significantly increased acute stress, with each additional nighttime sleep disruption increasing stress by 0.65 (β_5, p<.001) on the 0 – 100 VAS.

As shown in Figure 15, duty status significantly affected firefighters' between-subject variance in acute stress. Being "off night/day" had the smallest effect and being "on night/day" had the largest effect on between-subject variance in acute stress (α_0=4.55 [9.75 on VAS] and α_0+ α_1=5.57 [16.18 on VAS], respectively). There were significant differences in the effects of duty status on between-subject variance in acute stress between all types of duty status. Total nighttime sleep disruptions did not significantly affect between-subject variance in acute stress (α_4=-0.01 [9.71 on VAS], p=.781).

As shown in Figure 16, duty status significantly affected firefighters' within-subject variance in acute stress. Being "off night/day" had the smallest effect and being "off night/on day" had the largest effect on within-subject variance in acute stress (τ_0=4.39 [12.66 on VAS] and τ_0+τ_3=4.67 [14.55 on VAS], respectively). There were significant differences in within-subject variance by duty status, such that being "off night/day" resulted in significantly less within-subject variance in acute stress than any other type of duty status. There were no other significant differences between the types of duty status on within-subject variance in acute stress. Nighttime sleep disruptions did not affect within-subject variability in acute stress (τ_4=0.04 [12.93 on VAS], p=.054).

ICCs examining the proportion of variance in effects of duty status on acute stress were as follows: 1) "Off night/day": ICC=0.37; 2) "On night/day": ICC=0.55; 3) "On night/off day": ICC=0.41; and 4) "Off night/on day": ICC=0.46, indicating that, with the exception of when firefighters were "on night/day", a larger proportion of variance was due to the within-subject effects of duty status on acute stress (Figure 17).

There was a significant location effect on within-subject variability in stress, with higher mean stress corresponding with greater within-subject variability in stress ($\sigma_{\upsilon\omega}$=0.79, p<.001) (Figure 18). There was a significant random scale effect for stress (σ_{ω}^{2}=0.87, p<.001).

Mixed-effects location scale model – Tiredness

The model of best fit for tiredness indicated that duty status, recently taking a nap, and total nighttime sleep disruptions significantly predicted acute tiredness in firefighters. None of the other sleep-related variables or demographic characteristics significantly predicted acute tiredness. LL Diff Tests revealed that the stage 3 model was the model of best fit (LL Diff Test = 22194.95 – 21411.671 = 783.279). Table 8 includes the outcomes for the stage 3 MELSM for acute tiredness.

As shown in Figure 19, there were significant main effects of duty status on acute tiredness, with firefighters reporting the lowest levels of acute tiredness when they were "off night/day" (β_0=24.68) and the highest levels of acute tiredness when they were "on night/day" (β_0+β_1=30.00). There were significant differences in the effects of duty status on acute tiredness, such that being "off night/day" resulted in significantly lower acute tiredness compared to the other types of duty status. There were no other differences between the types of duty status on acute tiredness. Total nighttime sleep disruptions increased acute tiredness, with each additional disruption increasing acute tiredness by 1.74 (β_4, p<.011) on the 0 – 100 VAS. Recently taking a nap significantly decreased acute tiredness by 2.67 (β_5, p=.027) on the 0 – 100 VAS.

As shown in Figure 20, duty status significantly affected firefighters' between-subject variance in acute tiredness. Being "off night/day" had the smallest effect and being "on night/day" had the largest effect on between-subject variance in acute tiredness (α_0=4.97 [12.01 on VAS] and α_0+α_1=5.26 [13.87 on VAS], respectively). There were significant differences in the effects of duty status on between-subject variance in acute tiredness, such that being "off night/day" resulted in significantly lower between-subject variance in acute tiredness compared to being "on night/day" and "off night/on day". There were no other significant differences between the types of duty status on between-subject variance in acute tiredness.

Nighttime sleep disruptions increased between-subject variance in acute tiredness (α_4=0.10 [12.63 on VAS], p=.002). Recently taking a nap did not affect between-subject variance in acute tiredness (α_5=-0.10 [11.45 on VAS], p=.506).

As shown in Figure 21, duty status significantly affected within-subject variance in acute tiredness. Being "on night/day" had the smallest effect and being "on night/off day" had the largest effect on within-subject variance in acute tiredness (τ_0-τ_1=5.07 [15.94 on VAS] and τ_0+τ_2=5.55 [20.35 on VAS], respectively). There were significant differences in within-subject variance by duty status, such that being "on night/off day" resulted in significantly greater within-subject variance in acute tiredness than any other type of duty status. There were no other differences between the types of duty status on within-subject variance in acute tiredness. Nighttime sleep disruptions increased within-subject variability in acute tiredness (τ_4=0.08 [17.50 on VAS], p=.002). Recently taking a nap did not affect within-subject variance in acute tiredness (τ_5=-0.24 [14.89 on VAS], p=.066).

The ICCs examining the proportion of variance in effects of duty status on acute tiredness were as follows: 1) "Off night/day": ICC=0.34; 2) "On night/day": ICC=0.43; 3) "On night/off day": ICC=0.29; and 4) "Off night/on day": ICC=0.39, indicating that a larger proportion of variance was due to the within-subject effects of duty status on acute tiredness (Figure 22).

There was a significant location effect on within-subject variability in acute tiredness, with higher mean tiredness corresponding with greater within-subject variability in tiredness ($\sigma_{\upsilon\omega}$=0.65, p<.001) (Figure 23). There was a significant random scale effect for tiredness (σ_{ω}^2=0.72, p<.001).

Discussion

To our knowledge, this is the first study to use EMA to characterize firefighters' acute stress and tiredness by duty status and across multiple shift periods. In this way, our findings make a substantial contribution to the existing literature. These data provide a starting point for informing future studies focused on understanding predictors of firefighters' stress and tiredness, eventually paving the way for interventions to improve their stress and tiredness outcomes. The results supported our hypotheses that it

is feasible to capture acute stress and tiredness data in firefighters using a smartphone-based EMA approach, and that being on-duty increases acute stress and tiredness levels and variability in firefighters. Firefighters with higher mean stress and tiredness levels exhibited greater within-subject variability in stress and tiredness. Firefighters also demonstrated significant within-subject variability in stress and tiredness above and beyond the effects of duty status and other covariates. Total nighttime sleep disruptions increased stress and tiredness and increased between-subject and within-subject variability in tiredness, and recently taking a nap decreased tiredness in firefighters.

The relatively high feasibility score (70 out of 100) and EMA survey completion rate (61%) indicated that the smartphone-based EMA approach was feasible among Colorado firefighters. Previous EMA studies in firefighters neglected to report EMA survey completion rates (Gomes et al., 2013; Kaikkonen et al., 2017; Robinson et al., 2013; Robinson, Sunram-Lea, Leach, & Owen-Lynch, 2008; Rodrigues, Paiva, et al., 2018; Schwerdtfeger & Dick, 2019); however, our completion rate was similar to EMA studies in police officers, who completed 55-60% of EMA surveys (Tong et al., 2007; Yang, Ryu, Han, Oh, & Choi, 2018). While these completion rates are lower than EMA studies in the general population (completion rates 72-86%) (Jones, Taylor, Liao, Intille, & Dunton, 2017; J. M. Smyth et al., 2007), we expected lower rates due to the nature of firefighters' jobs (i.e. inability to answer EMA surveys when on calls) and intentionally used multiple assessment periods to capture sufficient data. Completion rates did not differ by duty status or time of day, indicating that researchers can feasibly capture EMA data in firefighters during the daytime, increasing the ecological validity of the results. The feasibility of capturing EMA data in firefighters when they are on- and off-duty is particularly important given the varied effects of duty status on firefighters' outcomes and previous calls in the literature for researchers to include off-duty assessments in firefighter studies (Rodrigues, Paiva, et al., 2018).

Our findings revealed that the combined effects of firefighters' duty status the prior night and during the day differentially affected their acute stress and tiredness levels and between-subject and within-subject variability. The fact that their prior night's duty status affected firefighters' daytime outcomes corresponds with research indicating that stress and fatigue levels in firefighters and other

emergency responders increase from the beginning to the end of a shift (Gomes et al., 2013; Patterson et al., 2019; Rodrigues, Kaiseler, et al., 2018; Rodrigues, Paiva, et al., 2018). Other research indicates that an individual's mean and variability in stress at bedtime (measured by cortisol) affects their subsequent day's mean and slope for cortisol (Proulx, Klee, & Oken, 2017). These previous studies align with our findings and support our approach in simultaneously examining the effects of the prior night's duty status and daytime duty status on firefighters' stress and tiredness.

While duty status differentially affected stress and tiredness outcomes, some common themes emerged. For example, firefighters exhibited their lowest acute stress and tiredness levels, as well as their lowest between-subject variability in stress and tiredness when they were "off night/day". Firefighters exhibited their highest acute stress and tiredness levels, as well as their highest between-subject variability in stress and tiredness when they were on-duty during the day, regardless of their prior night's duty status. These higher acute stress and tiredness levels when on-duty correspond with a study in police officers, who exhibited greater psychological and physiological stress when they were on-duty (Rodrigues, Kaiseler, et al., 2018), and with other research indicating that stress and fatigue levels increase from the beginning to end of a shift (Gomes et al., 2013; Patterson et al., 2019; Rodrigues, Kaiseler, et al., 2018; Rodrigues, Paiva, et al., 2018).

When firefighters were "off night/day", the within-subject effects of duty status accounted for a greater proportion of variability in acute stress (ICC=0.37) and tiredness (ICC=0.34) than the between-subject effects. This suggests that the different experiences firefighters have when they are off-duty increase their heterogeneity in acute stress and tiredness. This aligns with previous research indicating that firefighters' lives outside of the fire station, such as having a second job and their levels of social support, affect their perceived stress (Arbona, Pao, Long, & Olvera, 2017; Davidson & Moss, 2008; Regehr, 2009; Regehr, Dimitropoulos, Bright, George, & Henderson, 2005; Regehr, Hill, Knott, & Sault, 2003). Arbona et al. found that, among Black and Latino male firefighters, having a positive partner/spouse relationship correlated with lower perceived stress and, among Latino male firefighters, having a second job correlated with increased perceived stress (Arbona et al., 2017). Similar studies

indicate that firefighters' and other emergency responders' social support systems are vital for coping with trauma and other stressors (Davidson & Moss, 2008; Regehr, 2009; Regehr et al., 2005; Regehr et al., 2003). Clearly, firefighters' lives outside of their jobs affect their outcomes, which could explain the heterogeneity in acute stress and tiredness levels when firefighters are off-duty night/day. Future research examining how firefighters' lives outside of their jobs relate to stress and tiredness could aid researchers in identifying potential interventions for reducing firefighters' mean stress and stress variability.

When firefighters were "on night/day", the between-subject effects of duty status accounted for a greater proportion of variability in acute stress (ICC=0.55) than the within-subject effects. This suggests that the similar experiences firefighters have when they are on-duty result in more similar stress outcomes. For example, all firefighters participate in activities like waiting for a call, riding in the truck, or responding to an emergency (Rodrigues, Paiva, et al., 2018; Schwerdtfeger & Dick, 2019). Firefighters also respond similarly to and express common concerns regarding their experiences of critical incidents, such as traffic accidents, fires, and suicides (Jacobsson, Backteman-Erlanson, Brulin, & Hornsten, 2015). As such, firefighters' similar on-duty experiences, as well as their similar responses to and concerns regarding critical incidents, likely explain the greater similarity in their stress outcomes when they are "on night/day".

The between-subject effects of duty status on tiredness were greatest when firefighters were on-duty during the day, with a slightly greater contribution of between-subject effects when they were "on night/day" (ICC=0.43) versus "off night/on day" (ICC=0.39). These findings align with the stress outcomes in our study and support the idea that firefighters' similar experiences when they are on-duty during the day result in more similar tiredness outcomes.

In contrast, firefighters exhibited the greatest within-subject effects of duty status when they were "on night/off day" (ICC=0.29). This corresponds with research in other first responders, whose fatigue increased from the beginning to end of a shift (Patterson et al., 2019), and implies that the effects of being on-duty may extend beyond the end of the shift. These findings also suggest that an individual firefighter's experiences when on-duty during the night vary from shift-to-shift. For example, firefighters

in our study experienced 0 to 8 sleep disruptions on a given night. This wide range of sleep disruptions could affect variability in acute tiredness during the daytime. Indeed, our findings showed that nighttime sleep disruptions significantly increased acute tiredness and between-subject and within-subject variability in tiredness. Similarly, Takeyama et al. found that a greater frequency of nighttime ambulance calls increased subsequent stress and fatigue among firefighter paramedics (Takeyama et al., 2005), and other researchers found that responding to nighttime calls resulted in insufficient sleep, fragmented sleep, and greater fatigue in firefighters (Paterson, Aisbett, & Ferguson, 2016).

Finally, the different experiences firefighters have when they are off-duty might help explain the large within-subject effects of being "on night/off day" on tiredness. Previous research indicates that firefighters who work a second job experience poorer sleep quality (Billings & Focht, 2016) and are more likely to experience excessive daytime sleepiness (Haddock, Poston, Jitnarin, & Jahnke, 2013). Unfortunately, we did not ask firefighters to report whether they worked a second job, precluding us from examining said effects on tiredness in our sample. Overall, the different experiences firefighters have when they are off-duty, as well as the wide range of sleep disruptions they experience, could explain the large within-subject effects on acute tiredness when firefighters were "on night/off day".

Strengths and Limitations

The strengths of our study include using both on- and off-duty days in our study design and analyses. To our knowledge, this represents the only EMA study in firefighters including on- and off-duty days, multiple shift periods, and firefighters working different shift schedules (i.e. Kelly or 48/96 shifts). In contrast, other EMA studies in firefighters typically occurred over a single, 24-hour shift period and only included on-duty data (Gomes et al., 2013; Kaikkonen et al., 2017; Robinson et al., 2013; Rodrigues, Paiva, et al., 2018; Schwerdtfeger & Dick, 2019). Researchers specifically identified the need for EMA studies in firefighters to include more shift periods (Rodrigues, Paiva, et al., 2018; Schwerdtfeger & Dick, 2019) and on- and off-duty days (Rodrigues, Paiva, et al., 2018). Our study addressed both of these needs. Secondly, ours is one of only a few EMA studies examining firefighters' psychological outcomes, with one prior study examining anxiety (Robinson et al., 2013), one examining resilience and negative affect

(Schwerdtfeger & Dick, 2019), and a few studies examining perceived stress (Gomes et al., 2013; Kaikkonen et al., 2017; Rodrigues, Paiva, et al., 2018). Further, ours is the first EMA study to examine perceived tiredness in firefighters. Finally, to our knowledge, ours is one of only two EMA studies in firefighters that included females (Rodrigues, Paiva, et al., 2018).

Our study has some limitations. We used a convenience sample of Colorado, career firefighters that consisted predominantly of white male firefighters who worked either the Kelly or a 48/96 hour shift schedule, limiting the generalizability of our findings. Future studies should include a wider variety of races/ethnicities, particularly given that firefighters who are racial/ethnic minorities likely experience additional stressors related to their minority status, which may exacerbate the effects of firefighting on stress (Arbona et al., 2017). Future EMA studies should also include firefighters who work 24/48 hour shifts, as previous research suggests that firefighters who work 24/48 hour shifts experience better sleep quality (Billings & Focht, 2016) and are less likely to experience excessive daytime sleepiness (Haddock et al., 2013) than firefighters who work 48/96 hour shifts.

The focus on psychological stress is a potential limitation, because some firefighters indicated, via feedback on the feasibility survey (data not shown), that they experience anxiety rather than stress when they are on-duty. Indeed, one study in firefighter trainees revealed increased state anxiety immediately after they completed a 60 minute search and rescue and fire extinguishing exercise (Robinson et al., 2013). As such, focusing solely on stress, rather than including other similar psychological constructs like anxiety, may explain the relatively low stress levels in our sample. Finally, at the request of fire departments and to avoid disturbing firefighters' sleep, we only scheduled EMA surveys between 8AM and 9PM, precluding us from characterizing firefighters' stress and tiredness at nighttime.

Conclusions

In conclusion, our data indicate that it is feasible to capture acute stress and tiredness data in firefighters using a smartphone-based EMA approach. The combined effects of firefighters' duty status the prior night and day differentially affected their acute stress and tiredness levels, and between-subject

and within-subject variability. Firefighters had more similar stress and tiredness outcomes when they were on-duty and less similar outcomes when they were off-duty. This could be due to firefighters having more similar experiences to one another when they are on-duty and less similar experiences to one another when they are off-duty. Our study contributes to the literature by providing the first characterization of firefighters' acute stress and tiredness by duty status and across multiple shift periods. Future studies can build upon our findings to further examine predictors of firefighters' stress and tiredness to inform interventions to improve firefighters' stress, tiredness, and associated health outcomes.

Table 6. Participant demographics and descriptive statistics

Demographics	EMA Participants (N=39[a])
Age in years (Mean ± SD)	38.75 ± 10.60
Years in the Fire Service (Mean ± SD)	13.28 ± 9.41
Sex (n (%))	
Male	34 (87.18)
Female	4 (10.26)
Missing	1 (2.56)
Race/Ethnicity (n (%))	
White	33 (84.62)
Hispanic	4 (10.26)
African American	1 (2.56)
Missing	1 (2.56)
Marital Status (n (%))	
Married	29 (74.36)
Divorced	0 (0.00)
Single	10 (25.64)
Education (n (%))	
High School	0 (0.00)
Associate's Degree	10 (25.64)
Some College	10 (25.64)
College	17 (43.59)
Graduate School	1 (2.56)
Missing	1 (2.56)
Shift Schedule Type (n (%))	
Kelly Shift Schedule[b] 24 Hour Shifts	17 (43.59)
48 Hour Shifts[c]	22 (56.41)
Anthropometrics (Mean ± SD)	
Height (inches)	69.71 ± 2.94
Weight (pounds)	190.65 ± 28.51
BMI (kg/m^2)	27.53 ± 3.38
Weight Categories (n (%))	
Normal Weight	9 (23.08)
Overweight	19 (48.72)
Obese	10 (25.64)
Missing	2 (5.13)

[a]N includes all participants who were included in final analyses based on completing at least one EMA survey and working a shift schedule; [b]Two repetitions of 24 hours on/24 hours off, followed by 24 hours on/96 hours off; [c]48 hours on/96 hours off

Table 7. Two-level mixed-effects location scale model examining effects of duty status and nighttime sleep disruptions on acute stress in firefighters[a]

Beta – Regression Coefficients	**Estimate**	***SE***	***p***
Intercept β_1[b]	**16.267**	**1.585**	**<.001**
Duty Status (ref: "Off Night/Day")			
"On Night/Day" β_2	**8.200**	**1.24**	**<.001**
"On Night/Off Day" β_3	**2.553**	**0.666**	**<.001**
"Off Night/On Day" β_4	**6.827**	**0.745**	**<.001**
Number of Nighttime Sleep Disruptions β_5[c]	**0.650**	**0.166**	**<.001**
Alpha – Between-Subject Variance			
Intercept α_0[b]	**4.554**	**0.237**	**<.001**
Duty Status (ref: "Off Night/Day")			
"On Night/Day" α_1	**1.014**	**0.107**	**<.001**
"On Night/Off Day" α_2	**0.389**	**0.089**	**<.001**
"Off Night/On Day" α_3	**0.623**	**0.071**	**<.001**
Number of Nighttime Sleep Disruptions α_4[c]	-0.007	0.024	.781
Tau – Within-Subject Variance			
Intercept τ_0[b]	**4.392**	**0.204**	**<.001**
Duty Status (ref: "Off Night/Day")			
"On Night/Day" τ_1	**0.271**	**0.095**	**.004**
"On Night/Off Day" τ_2	**0.242**	**0.085**	**.004**
"Off Night/On Day" τ_3	**0.278**	**0.077**	**<.001**
Number of Nighttime Sleep Disruptions τ_4[c]	0.042	0.022	.054
Random Location (Mean) Effect on Within-Subject Variance in Stress ($\sigma_{v\omega}$)	**0.786**	**0.181**	**<.001**
Random Scale Effect (σ_{ω}^2)	**0.868**	**0.115**	**<.001**

[a]Level one of the model included 3172 observations (EMA survey responses) nested into 39 level two clusters (participants); [b]The intercept values represent the predicted stress level (0 – 100) for a firefighter who was off duty the prior night and off duty during the day time, experienced zero nighttime sleep disruptions, and did not recently sleep; [c]Number of nighttime sleep disruptions ranged from 0 to 7 or more disruptions.

Table 8. Two-level mixed-effects location scale model examining effects of duty status, nighttime sleep disruptions, and recent daytime sleep on acute tiredness in firefighters[a]

Beta – Regression Coefficients	**Estimate**	***SE***	***p***
Intercept β_0[b]	**24.681**	**2.049**	**<.001**
Duty Status (ref: "Off Night/Day")			
"On Night/Day" β_2	**5.323**	**1.090**	**<.001**
"On Night/Off Day" β_3	**4.778**	**0.974**	**<.001**
"Off Night/On Day" β_4	**4.526**	**0.759**	**<.001**
Number of Nighttime Sleep Disruptions β_4[c]	**1.743**	**0.317**	**<.001**
Recent Nap β_5[d]	**-2.670**	**1.219**	**.027**
Alpha – Between-Subject Variance			
Intercept α_0[b]	**4.971**	**0.250**	**<.001**
Duty Status (ref: "Off Night/Day")			
"On Night/Day" α_1	**0.289**	**0.115**	**.012**
"On Night/Off Day" α_2	0.146	0.107	.173
"Off Night/On Day" α_3	**0.218**	**0.081**	**.007**
Number of Nighttime Sleep Disruptions α_4[c]	**0.100**	**0.032**	**.002**
Recent Nap α_5[d]	-0.095	0.143	.506
Tau – Within-Subject Variance			
Intercept τ_0[b]	**5.173**	**0.175**	**<.001**
Duty Status (ref: "Off Night/Day")			
"On Night/Day" τ_1	-0.108	0.103	.296
"On Night/Off Day" τ_2	**0.381**	**0.092**	**<.001**
"Off Night/On Day" τ_3	-0.029	0.079	.713
Number of Nighttime Sleep Disruptions τ_4[c]	**0.080**	**0.026**	**.002**
Recent Nap τ_5[d]	-0.244	0.133	.066
Random Location (Mean) Effect on Within-Subject Variance in Tiredness $(\sigma_{\upsilon\omega})$	**0.651**	**0.150**	**<.001**
Random Scale Effect (σ_{ω}^2)	**0.722**	**0.094**	**<.001**

[a]Level one of the model included 2613 observations (EMA survey responses) nested into 38 level two clusters (participants); [b]The intercept values represent the predicted tiredness level (0 – 100) for a firefighter who was off duty the prior night and off duty during the day time, experienced zero nighttime sleep disruptions, and did not recently sleep; [c]Number of nighttime sleep disruptions ranged from 0 to 7 or more disruptions; [d]Recent daytime sleep reflects whether the participant indicated they had slept since their last assessment and specifically reflects daytime sleep bouts.

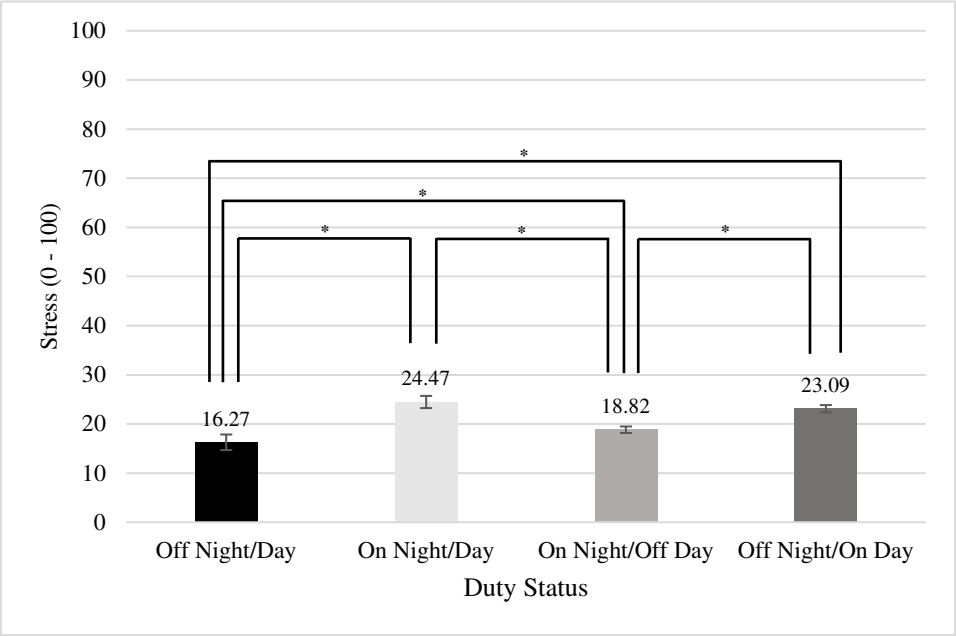


Figure 15. Effects of duty status on acute stress in firefighters

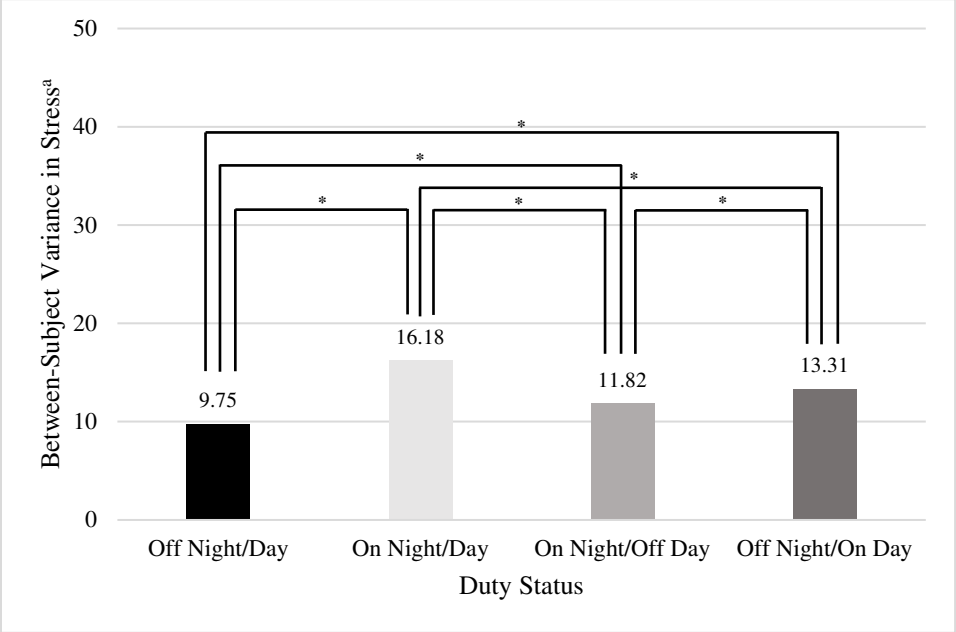


Figure 16. Effects of duty status on between-subject variance in acute stress

[a]Values for between-subject variance in stress were converted from the log-linear values reported in the model outcomes to the 0 – 100 VAS for ease of interpretation (Hedeker & Nordgren, 2013).

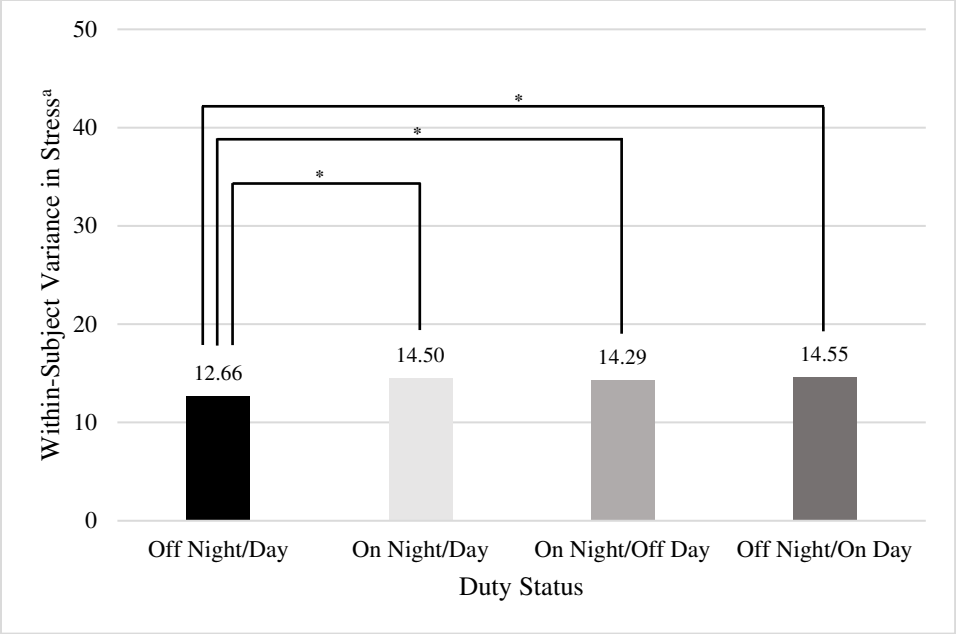


Figure 17. Effects of duty status on within-subject variance in acute stress

[a]Values for within-subject variance in stress were converted from the log-linear values reported in the model outcomes to the 0 – 100 VAS for ease of interpretation (Hedeker & Nordgren, 2013).

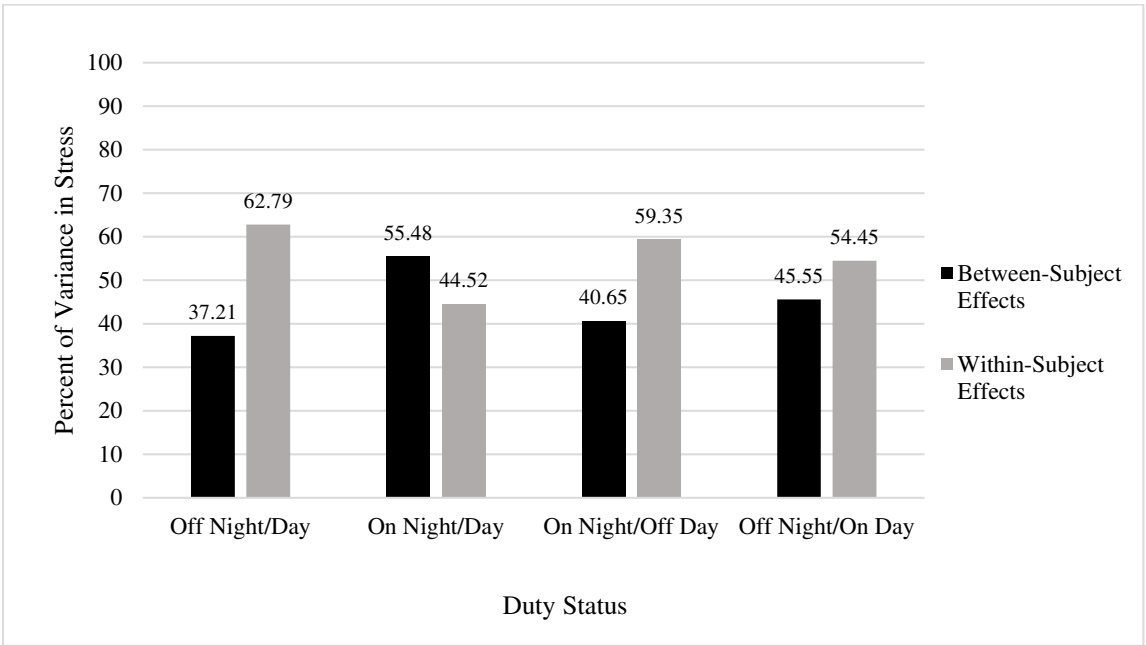


Figure 18. Proportion of variability in acute stress due to between-subject versus within-subject effects of duty status

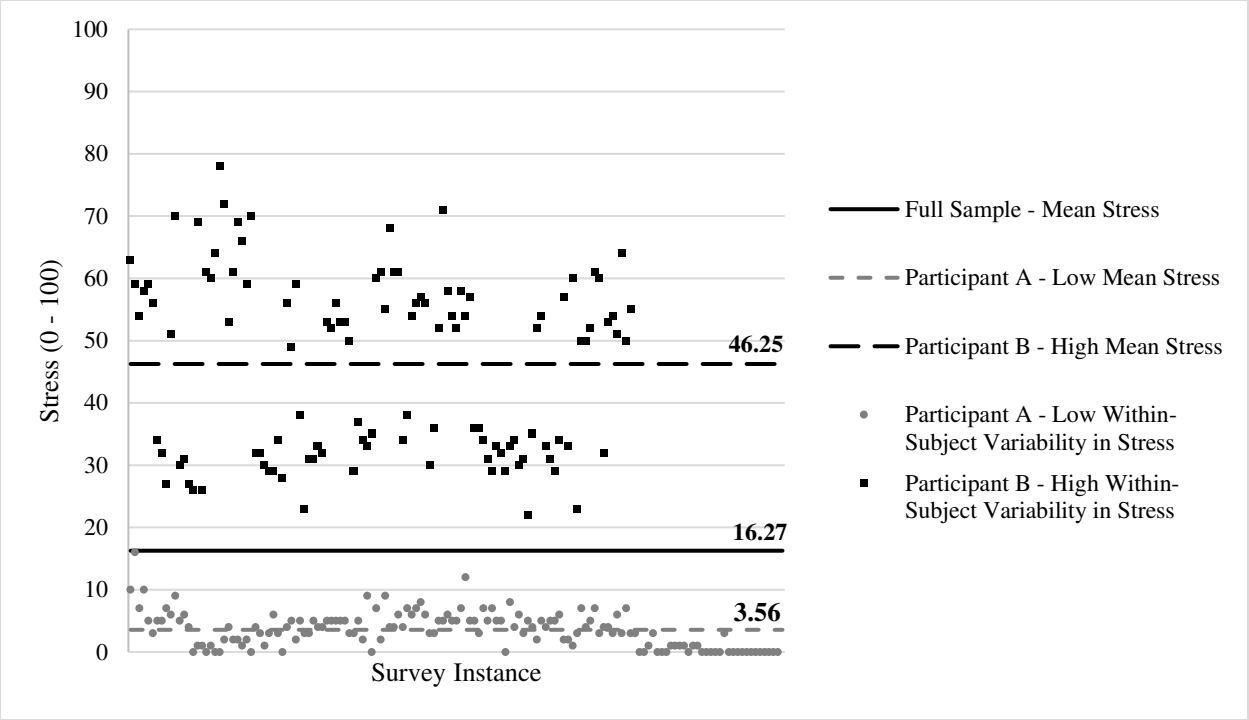


Figure 19. Significant location effect on within-subject variance in acute stress

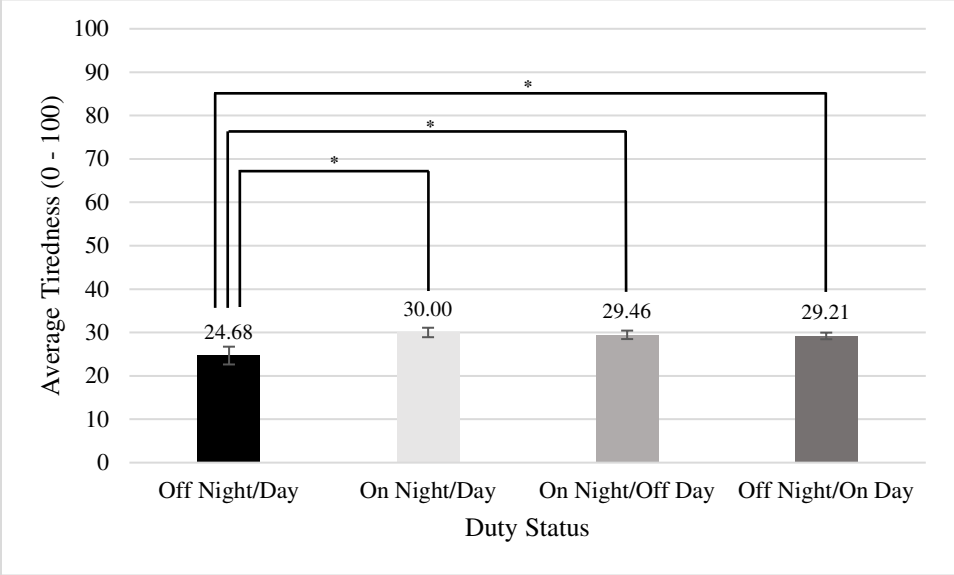


Figure 20. Effects of duty status on acute tiredness in firefighters

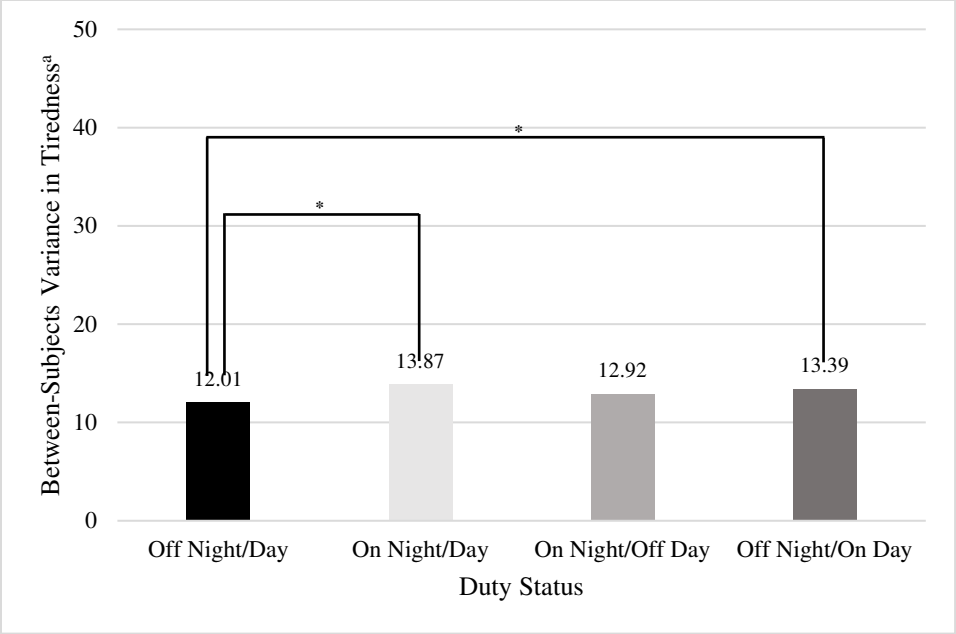


Figure 21. Effects of duty status on between-subject variance in acute tiredness

[a]Values for between-subject variance in tiredness were converted from the log-linear values reported in the model outcomes to the 0 – 100 VAS for ease of interpretation (Hedeker & Nordgren, 2013).

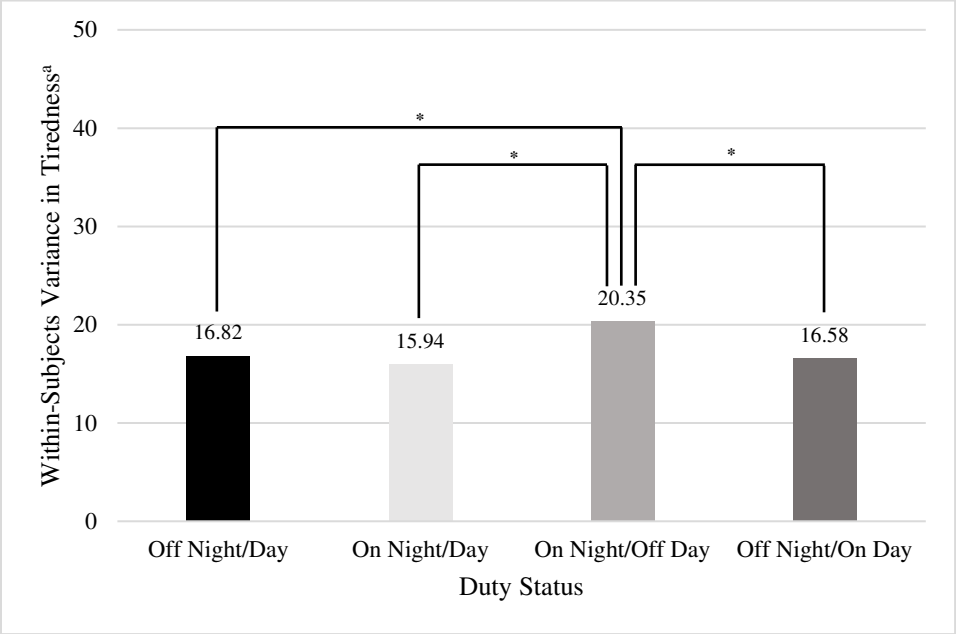


Figure 22. Effects of duty status on within-subject variance in acute tiredness

[a]Values for within-subject variance in tiredness were converted from the log-linear values reported in the model outcomes to the 0 – 100 VAS for ease of interpretation (Hedeker & Nordgren, 2013).

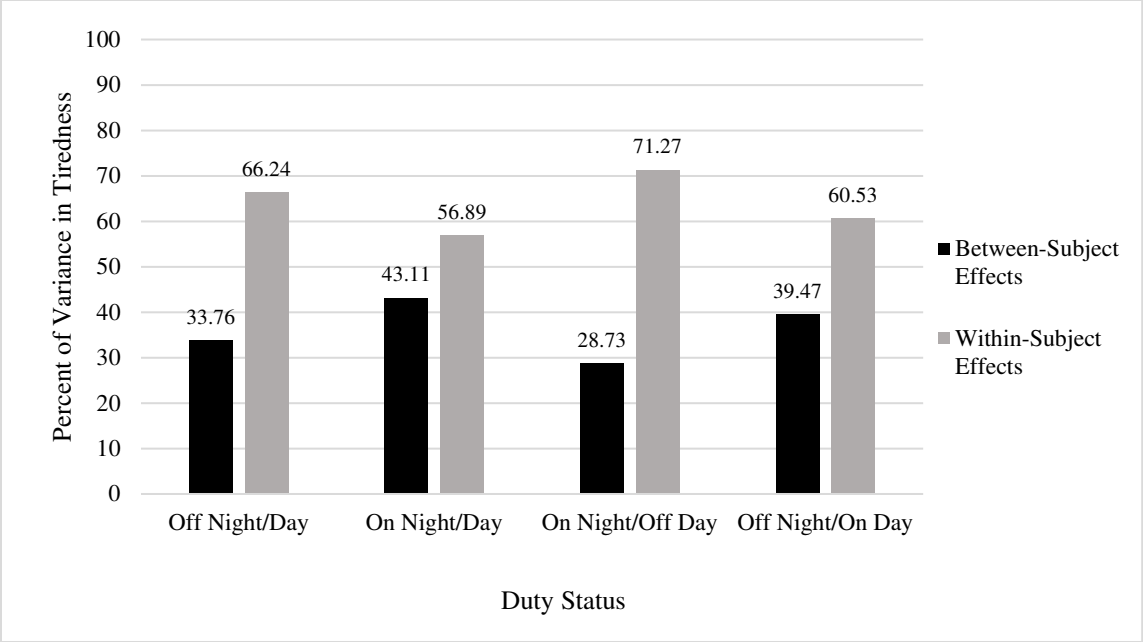


Figure 23. Proportion of variability in tiredness due to between-subject versus within-subjects effects of duty status

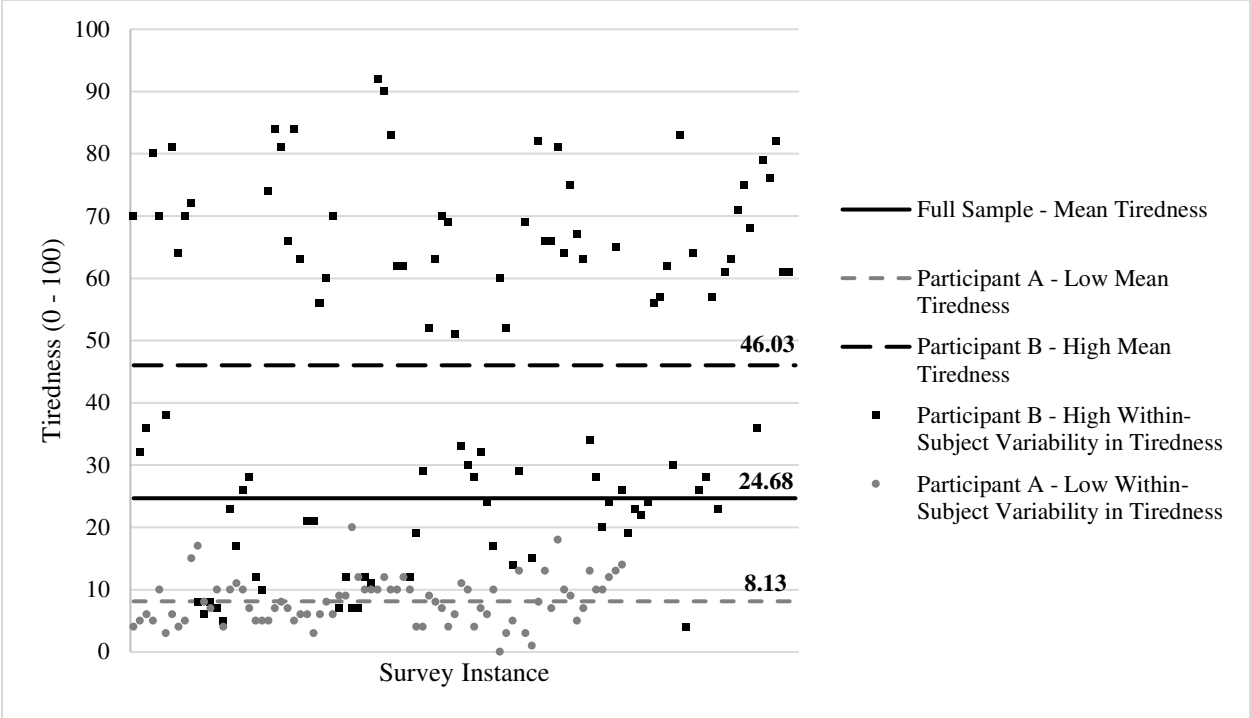


Figure 24. Significant location effect on within-subject variance in tiredness

CHAPTER 5 – CONCLUSIONS

This dissertation provided concrete examples of how researchers in the health sciences can combine data scientists' three areas of knowledge: 1) Substantive Expertise; 2) Technology & Computer Science; and 3) Statistics & Math (Wickham & Grolemund, 2017), to inform the collection, management, analysis, and interpretation of data related to unmodifiable and psychosocial determinants of health, health behaviors, and health outcomes.

Study 1, "Migration of an ongoing, community-based project in firefighters to the Research Electronic Data Capture (REDCap) platform", demonstrated how technology and computer science skills enabled the development of a sophisticated REDCap project (P. A. Harris et al., 2009) that employed real-time electronic data capture, automated surveys, branching logic, and calculated fields, etc., to increase the efficiency of data collection, improve data management and quality control/assurance, and accommodate the Firefighter Testing Program's (FTP) varied approach to repeated measures, specific reporting needs, and research goals. This study demonstrated the challenges related to creating an electronic database that supports proper data management and quality control/assurance measures, which is necessary so that data scientists can trust research outcomes (Bowne-Anderson, 2018). Migrating the FTP from paper-based data capture to REDCap required 15 months of project development, with subsequent field-testing and ongoing data collection resulting in continued changes to the FTP REDCap project one-year after its initial launch, reinforcing previous research suggesting that data scientists use approximately 80% of their time finding, cleaning, and/or organizing data (Bowne-Anderson, 2018; Crowdflower, 2016). While this study primarily demonstrated technology/computer science skills, it is important to note that substantive expertise related to measuring unmodifiable and psychosocial determinants of health, fitness, and cardiovascular disease risk factors, as well as statistical knowledge, significantly informed the development of the FTP REDCap project. For example, such knowledge informed the decision to discontinue measuring psychosocial variables related to type A personality, forgiveness, etc. in favor of using more well-established and relevant measures for firefighters, such as

the occupational stress, measured via the Sources of Occupational Stress-13. Statistical knowledge regarding researchers' needs for clearly defined and coded data informed the decision to transition from qualitative to quantitative measures of outcomes, like hospitalizations/surgeries and family history of heart disease, for ease of data analyses. Overall, study 1 demonstrates that creating an efficient and usable electronic database requires data scientists to draw upon their entire skill set, including technological/computer science skills, statistical skills, and substantive expertise.

Study 2, "Comparing the activPAL software's Primary Time in Bed Algorithm against self-report and van der Berg's algorithm", demonstrated how technology can be used to examine individuals' health behaviors, specifically examining the utility of the activPAL monitor (PAL Technologies Ltd., 2010) for measuring individuals' primary time spent lying down (a proxy for sleep) compared to the commonly used measure of self-report (Devine et al., 2005; Quante et al., 2015) and the van der Berg algorithm. The results of study 2 indicated that the activPAL algorithm was not equivalent to self-report or the van der Berg algorithm for detecting time in bed. However, the activPAL algorithm was equivalent to self-report for identifying bed time, and was equivalent to the van der Berg algorithm for identifying wake time. Despite this lack of equivalence, knowledge regarding how the activPAL monitor measures movement and body posture (PAL Technologies Ltd., 2010) and how the activPAL algorithm identifies primary time in bed (PAL Technologies Ltd., 2019), combined with substantive expertise related to lying down and sleep-related behaviors informed the conclusion that the activPAL algorithm only requires minimal updates to achieve equivalence with self-report and the van der Berg algorithm. For example, we determined that lying down with high levels of stillness prior to actually going to bed caused the activPAL to misidentify bed time, resulting in overestimating time in bed, which is a common challenge when using accelerometers to identify sleep-related behaviors (Gibbs & Kline, 2018), as well as when distinguishing sedentary behaviors surrounding sleep from sleep itself (Quante et al., 2015). Additionally, we determined that wakefulness after sleep onset resulted in the activPAL inaccurately identifying wake time, resulting in underestimating time in bed, which is another challenge common to using accelerometers for sleep-related measures (Gibbs & Kline, 2018; Quante et al., 2015). Despite these

short-comings, only minor adjustments are needed to improve the activPAL algorithm for time in bed. The need for minor adjustments and the fact that activPAL users can manually adjust bed and wake times led to our conclusion that activPAL users can start taking advantage of the new algorithm. We also concluded that the new time in bed algorithm enhances the utility of using the activPAL for examining 24-hour movement patterns, including sleep, in free-living individuals. Overall, the study demonstrated how data scientists can leverage technology to measure health behaviors and use their substantive expertise to inform the interpretation of health behavior data.

Study 3, "Motivation and planning effects on physical activity during the adolescent-to-adult-transition", demonstrated that statistics and math can be used to examine how unmodifiable determinants, including sex and race/ethnicity, and psychosocial determinants, including autonomous motivation, controlled motivation, and physical activity planning, relate to physical activity participation in adolescents transitioning into early adulthood. The results of the piece-wise growth model indicated that physical activity participation during the adolescent-to-adult transition was characterized by two distinct phases, with a transient increase in physical activity between one and two years post-high school. Additionally, unmodifiable characteristics, like sex and race/ethnicity significantly affected baseline physical activity levels, with females, African Americans and Hispanics participating in significantly less physical activity than males and Whites, respectively. We also found that the psychosocial determinants of autonomous motivation and physical activity planning were significantly and positively associated with physical activity; whereas, controlled motivation was not associated physical activity. Statistical knowledge strongly informed the modeling approach used in this study, and substantive expertise informed the decision to examine the effects of sex and race/ethnicity, rather than controlling for them, as research consistently indicates differences in physical activity by sex (Bauman et al., 2012; Healy et al., 2011; Luke et al., 2011; Mozaffarian et al., 2015; Troiano et al., 2008) and race/ethnicity (Kann et al., 2014; Mozaffarian et al., 2015). Substantive expertise also informed the decision to examine the individual effects of autonomous motivation (Barbeau et al., 2009; Dishman et al., 2018; Teixeira et al., 2012), controlled motivation (Barbeau et al., 2009; Dishman et al., 2018; Teixeira et al., 2012), and

physical activity planning on physical activity (Ajzen, 1991; Blanchard et al., 2002; Fishbein & Ajzen, 1980; Maddux, 1993; Sniehotta et al., 2005). The results of study 3 reinforced the value of data scientists' ability to identify appropriate statistical models for examining health behavior outcomes, and the value of using their substantive expertise to inform which variables should be examined as potential predictors of health behaviors, like physical activity.

Study 4, "Using ecological momentary assessment to examine the effects of duty status on acute stress and tiredness in firefighters: A pilot study", provided an example of how data scientists can combine their technological and statistical skills with substantive expertise to examine psychosocial determinants of health behaviors. This study leveraged smartphone technology to capture repeated measures of stress and tiredness in real-time and in an individual's natural environment so that we could examine acute stress and tiredness, and between- and within-person variability in stress and tiredness among a sample of career firefighters. We found that it was feasible to capture acute stress and tiredness data in firefighters using a smartphone-based ecological momentary assessment approach. Additionally, the mixed-effects location scale models revealed that the combined effects of firefighters' duty status the prior night and during the current day differentially affected their acute stress and tiredness levels, and between-subject and within-subject variability in stress and tiredness. Substantive expertise regarding the effects of psychological stress (Dean et al., 2003; Guidotti, 1992; Roy et al., 1998) and tiredness (Kashani et al., 2012; Wolk et al., 2005) on health outcomes, as well as knowledge of firefighters' experiences with stress (Guidotti, 1992; Soteriades et al., 2011) (Dean et al., 2003) and sleep disturbances (Akerstedt et al., 2002; Akerstedt et al., 2007; Akerstedt et al., 2012; Kashani et al., 2012), strongly informed the design of this study, including the decision to use ecological momentary assessment (Shiffman et al., 2008; J. M. Smyth & Stone, 2003). This study also demonstrated the value of statistical knowledge, particularly because other modeling approaches would have precluded the ability to extract information about the unique effects of firefighters' duty status on their between- and within-subject variability in stress and tiredness, which were the most meaningful outcomes of the study.

The studies in this dissertation demonstrated how skills in technology/computer science, statistics/math, and substantive expertise in the health sciences can inform the collection, management, analysis, and interpretation of data related to unmodifiable and psychosocial determinants of health, health behaviors, and health outcomes (Wickham & Grolemund, 2017). They also demonstrated how these skills can be applied to research in a variety of populations and research using various methodological and statistical approaches. Overall, this dissertation supports the assertion that we should intentionally foster the development of data scientists within the health sciences and capitalize on data scientists' skills to promote progress in research, clinical practice, and public health, with the long-term goal of improving human health.

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