Mobility Limitation and Body Mass Index: Identifying Impact and Environmental Moderating Effects

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THESIS

Submitted as partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Public Health Sciences (Health Policy and Administration)
in the Graduate College of the
University of Illinois at Chicago, 2019

Chicago, Illinois

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ACKNOWLDGEMENTS

I would like to thank the many people who helped me on this endeavor to complete my PhD. I want to thank my chair and advisor, Dr. Lisa Powell for providing thoughtful guidance and mentorship in completing this thesis. I greatly appreciate your expert insight into both scholarship and communication that I plan to carry forward in all my work. I'd like to thank Dr. Shannon Zenk and Dr. Elizabeth Tarlov for providing an opportunity to work with a novel dataset from the Weight and Veterans Environment study and helping to orient and guide my study along the way. Dr. Tarlov also went above and beyond to provide amazing guidance and mentorship in using a healthcare data and helping to orient me to the ways of the Department of Veterans Affairs. I am sure I would have been quite lost without having Dr. Tarlov to provide clearly marked signs along the path of using the data, analyzing the data, and interpreting my results. I am greatly indebted and hope to continue a collaboration with the VA. From the Hines, VA, I'd also like to thank Lishan Cao and Brian Bartle who helped in preparing data and orienting me to have a full understanding of how to use the many datasets I incorporated in this thesis. I want to thank Dr. Zeynep Isgor and Dr. Kiyoshi Yamaki for providing important technical and substantive advice regarding my analysis and theoretical connections. Dr. James Rimmer was also a major influence in the motivation for this dissertation as it follows closely the goals and mission of his work. He took a chance on an urban planner with no disability experience and continues to be a foundation from which to build my career.

Of course, my family was the energy that fueled the engine of writing this thesis. I lovingly share this accomplishment with my wife, Amy. You were supportive through some of the darkest times and celebratory in the brightest. You saw the light way before I could and saw that I had it in me to go this route. I thank my daughters, Orli, Noa, and Mara who had such patience and understanding for my time spent working towards this thesis and for helping to make me laugh, jump, and run so that I could distract myself from the stress that a thesis can incite. Finally to my parents, in-laws, brothers, friends, and peers who provided support to me and family all along the way, I thank you deeply.

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LIST OF ABBREVIATIONS

ACS	American Community Survey
ADA	American’s with Disabilities Act
ADL	Activity of Daily Living
AOR	Adjusted Odds Ratio
AUC	Area Under the Curve
BIC	Bayesian Information Criterion
BMI	Body Mass Index
BRFSS	Behavioral Risk Factor Surveillance System
CDC	Centers for Disease Control and Prevention
CDW	Corporate Data Warehouse
COPD	Chronic Obstructive Pulmonary Disease
DME	Durable Medical Equipment
GIS	Geographic Information Systems
HCPCS	Healthcare Common Procedures Coding System
ICD9	International Classification of Diseases, Ninth Revision
ICF	International Classification of Functioning, Disability and Health
LR+	Likelihood Ratio Positive
LR-	Likelihood Ratio Negative
MCBS	Medicare Current Beneficiary Survey
NCBDDD	National Center on Birth Defects and Development Disabilities
NHANES	National Health and Nutrition Examination Survey
NHIS	National Health Interview Survey
NIH	National Institutes of Health
NPPD	National Patient Prosthetics Database
NPV	Negative Predictive Value
OLS	Ordinary Least Squares
OR	Odds Ratio
PPV	Positive Predictive Value
ROC	Receiver Operator Characteristic curves
SCI	Spinal Cord Injury
SES	Socio-economic status
VA	Department of Veterans Affairs
VHA	Veteran’s Health Administration

LIST OF ABBREVIATIONS (continued)

VISN	Veterans Integrated Services Networks
WAVES	Weight and Veteran’s Environment Study
WHO	World Health Organization

SUMMARY

Obesity is more prevalent among people with mobility limitations than those without (An, Andrade, & Chiu, 2015; Reichard, Stolzle, & Fox, 2011). Given the many consequences of obesity for later life health and quality of life and its potential to worsen mobility limitation itself, finding ways to help people avoid obesity is an important public health goal (Fox, Witten, & Lullo, 2013; Krahn, Walker, & Correa-De-Araujo, 2015). However, much of what we know about mobility limitation and obesity comes from cross-sectional studies and suggests that obesity is higher among people with mobility limitations compared to those without. Although obesity may be higher, there is not sufficient evidence to know whether the strong associations observed between mobility limitation and body mass index (BMI) are a result of the mobility limitation or whether there are unobserved/unmeasured factors that are the cause of the high rate of obesity among people with mobility limitations. On the one hand, it may be that people with mobility limitation are becoming obese. However, the reverse is also possible that people who are obese are developing mobility limitations. It is important for public health efforts seeking to reduce obesity among people with mobility limitations to better understand this relationship. The current literature on mobility limitation leading to obesity is minimal and has not addressed unobserved heterogeneity that may bias results. Because a limited number of studies have examined the effect of mobility limitation on BMI over time, it is unclear whether people with mobility limitations are at a higher risk for increases in BMI and obesity. Some initial research has indicated that there are important contextual factors that influence the magnitude and direction of the effect of mobility limitation on BMI.

One important contextual factor that previous literature has described as important for people with mobility limitations is neighborhood walkability. Although research has suggested that neighborhood walkability may play an important role in helping to curb the obesity epidemic in the US population (Chandrabose et al., 2019; Sallis, Floyd, Rodríguez, & Saelens, 2012), there is no existing research on how neighborhood walkability impacts body weight for people with mobility limitations. A challenge in using data developed from healthcare administrative sources is the lack of a valid approach to distinguishing between those who do and do not have a mobility limitation. Overcoming this challenge opens up new opportunities for research using healthcare administrative data to study and monitor the health of people with mobility limitations. The overall purpose of this dissertation was to better understand the effect of a mobility limitation on BMI and how that effect is modified in the context of personal and environmental factors. This dissertation is written as three separate studies. In the first chapter, I describe the development and evaluation of an algorithm for identifying people with mobility limitations using healthcare administrative data. In the second chapter, I examine the effect of mobility limitation on BMI in a large, national sample of veterans, and in the third chapter, I examine whether neighborhood walkability moderates the effect of mobility limitation on BMI.

In this thesis, I use the International Classification of Functioning, Disability and Health (ICF) (World Health Organization, 2001) as a conceptual model for understanding factors that influence mobility limitation and for exploring how mobility limitation might affect BMI in the context of personal and neighborhood environmental factors. The ICF helps in framing these relationships and is linked to the empirical models used in this study. In all three chapters, I also use data from the Weight and Veterans' Environment Study (WAVES). WAVES data provide a unique opportunity to study change in BMI over time controlling for both contextual factors and unobserved heterogeneity. WAVES was an NIH R01 (R01CA172726, VA IIR 13-085) study that developed a large longitudinal cohort of 3.2 million veterans using data derived from healthcare administrative sources on individuals and public and private sources of information on the neighborhood environment (Zenk et al., 2018).

In the first chapter, I address the challenge of identifying people with mobility limitations in healthcare administrative data by developing a predictive mobility limitation algorithm. Current approaches to studying mobility limitation are limited because there are few longitudinal surveys that ask about mobility limitation, there are differing definitions of mobility limitation, and the sample sizes in many studies are usually small (Livermore, 2007). As a result, there are limited opportunities for studying the health of people with mobility limitations over time. Healthcare administrative data offer a new potential source for studying healthcare services and outcomes for people with mobility limitation. However, the current sets of codes related to mobility limitation are limited and do not account for the complex nature of mobility limitations, which require data on health conditions, assistive devices, personal characteristics and environmental factors; all of which contribute to and reflect aspects of a mobility limitation but are not sufficient to identify mobility limitation on their own (Iezzoni, 2002). The purpose of this study was to develop a mobility limitation algorithm that could be used to identify and study people with mobility limitations using healthcare administrative data.

I used responses on self-reported mobility limitation from the Medicare Current Beneficiary Survey as a gold standard for mobility limitation. I linked the responses to healthcare administrative data on assistive devices, diagnoses of health conditions related to mobility limitation, demographics, and healthcare utilization. I used an iterative process to develop a logistic regression model that was best at correctly classifying subjects as having a mobility limitation or not. I evaluated the performance of both multi-level and binary approaches to operationalizing mobility limitation. I found that the multi-level approach did not perform well at correctly classifying the level mobility limitation, but the binary approach had good sensitivity and specificity.

Chapter one contributed to the literature as a new approach to studying mobility limitation in large samples. The mobility limitation algorithm allows researchers to take advantage of the opportunity of healthcare administrative data to study health service and outcomes for people with mobility limitations, although further refinement and validation are necessary. The binary predictive algorithm is used in the second and third chapters of this dissertation to classify the WAVES sample as having a mobility limitation or not. Researchers in the fields of public health, rehabilitation, occupational therapy, physical therapy, and disability studies, can utilize the algorithm to identify individuals with mobility limitations using similar healthcare administrative data.

In the second chapter, I examined the effect of mobility limitation on BMI using a large national sample of veterans from WAVES. A challenge to studying the effect of mobility limitation on BMI is reverse causality – mobility limitation can cause obesity and obesity can cause mobility limitation. The estimate obtained from cross-sectional models includes both the effect of mobility limitation on BMI and the effect of high BMI causing a mobility limitation (de Munter, Tynelius, Ahlstrom, & Rasmussen, 2016). There are mixed results among longitudinal studies that have examined the effect of mobility limitation on BMI. Some of the research suggests that there are large effects on BMI for people with specific health conditions related to mobility limitations, and smaller effects for studies that used population based surveys. However, both sets of studies are limited in how reverse causality was addressed as well as how unobserved factors that threaten causal interpretation were addressed. The purpose of this study was to examine the effect of mobility limitation on BMI in order to understand if people with mobility limitations are at higher risk for weight gain compared to those without mobility limitations. Additionally, I examined whether there was a higher risk of increased BMI as a result of a mobility limitation for people with certain personal characteristics related to age, comorbidities, and baseline BMI category.

I conducted a longitudinal panel data analysis of the effect of mobility limitation on BMI over a 6 year period using data from WAVES. I used individual fixed effects to control for all time-invariant unobserved variables as well as a lag of mobility limitation to ensure that the mobility limitation came before the BMI measurement. I compared fixed-effects models with pooled cross-sectional models and conducted stratified analysis based on age group, level of comorbidities, and baseline BMI category.

I found that in pooled cross-sectional models there was a strong association between mobility limitation and BMI, but in fixed-effects models, the magnitude of the effect was only a small increase. The results held across several sensitivity analyses. Furthermore, the effect of mobility limitation on BMI varied by age group. There was a higher effect for younger ages and then the effect decreased with each

age group. The effect was also larger for those with many comorbidities. Lastly, the effect of mobility limitation on BMI was higher among those who were underweight at baseline but mostly similar effect sizes in the other baseline BMI categories.

This study addressed important threats to causal interpretation that had not been dealt with in previous studies. The estimates obtained from fixed-effects models used in this study can be interpreted as causal based on the assumption that there are no time-varying omitted variables that are correlated with mobility limitation and BMI. Results suggested that the effect of mobility limitation on BMI is a small increase and that there is some variation across age and comorbidities. These results imply that having a mobility limitation is not causing the high rates of obesity among people with mobility limitations, but that this is caused by the unobserved factors that were eliminated in the fixed-effects models. Interventions seeking to prevent obesity among people with mobility limitations would benefit from targeting younger age groups who may be at a higher risk for increased BMI based on results from this study. Further research is needed that can assess how the degree of mobility limitation might also result in a differential impact on BMI.

In the third chapter, I examined the role of neighborhood walkability as a moderator of the effect of mobility limitation on BMI. Previous research has suggested that there is an association between neighborhood walkability and physical activity and BMI. However, there is a lack of studies on people with mobility limitations. Based on the International Classification of Functioning, Disability and Health as well as literature on the neighborhood environment and disability, the neighborhood environment could be an important moderator of the effect of mobility limitation on BMI. The purpose of this study was to examine whether the effect of mobility limitation on BMI is moderated by the neighborhood environment.

I leveraged WAVES time-varying data on walkability and other measures of the food and physical activity environment within 1-mile of veteran’s homes. Similar to the second study, I used fixed-effects models with a lag for mobility limitation and BMI as the outcome. In this third study, I added an interaction term between mobility limitation and quartiles of walkability to study if the effect of mobility limitation on BMI changed based on low to high walkability. I ran separate models for individuals who never moved during the study period and whose variation in walkability came only from changes in the neighborhood environment instead of also including individual preferences. Because neighborhood poverty may also moderate the effect of walkability on BMI, I also examined if the effect of mobility limitation interacting with walkability varied by different levels of neighborhood poverty.

I found that neighborhood walkability moderated the effect of mobility limitation on BMI. For veterans in low-walkability neighborhoods, there was a higher effect of mobility limitation on BMI and the effect of mobility limitation on BMI became insignificant in the highest walkability quartile. This pattern held for those who never moved during the study period. Under the assumption that there are no time-varying omitted variables that are correlated with mobility limitation, walkability, and BMI, the results can be interpreted as causal. Additionally, this study found a deleterious effect of mobility limitation on BMI for those who were in low-walkability, high-poverty neighborhoods as well as for older adults who lived in low-walkability neighborhoods. Results from this third chapter suggest that low-walkability neighborhoods present additional risks for increased BMI among people with mobility limitations. Results suggest that policy and environmental strategies to improve walkability, such as by increasing destinations that people can walk to or improving the street network, can provide positive health benefits to people with mobility limitations.

I. DEVELOPMENT OF A PREDICTIVE ALGORITHM TO IDENTIFY PEOPLE WITH MOBILITY LIMITATIONS USING HEALTHCARE ADMINISTRATIVE DATA

A. Introduction

Healthcare administrative data provide important opportunities for the field of public health to track and monitor healthcare access and quality, utilization and outcomes (Birkhead, Klompas, & Shah, 2015; Casey, Schwartz, Stewart, & Adler, 2016). Healthcare administrative data include electronic health records (EHR) and other data generated for billing and quality improvement purposes (Iezzoni, 1997). Proponents promote healthcare administrative data as a supplement to existing approaches for population health surveillance and monitoring that traditionally rely on the use of State (e.g. Behavioral Risk Factor Surveillance System (BRFSS)) and National (e.g. National Health and Nutrition Examination Survey (NHANES)) surveys (Klompas et al., 2017). Healthcare administrative data are also increasingly being used to define cohorts with specific characteristics or conditions for research and evaluation (Shivade et al., 2013). One important group that could benefit from new research approaches that leverage healthcare administrative data are people with disabilities (Turk & McDermott, 2018).

People with disabilities have been described as a health disparity population because their access to care and health outcomes are far worse than people without disabilities (Krahn et al., 2015). The largest group within the population who report a disability are people with a mobility limitation, who comprise 31.5 million people or 13% of US adults (Courtney-Long et al., 2015). Having a mobility limitation is associated with poor self-rated health (Froehlich-Grobe, Jones, Businelle, Kendzor, & Balasubramanian, 2016; Reichard et al., 2011), as well as reports of greater numbers of chronic conditions, including heart disease, diabetes, and high blood pressure (Reichard et al., 2011). Increased risk of injuries and mortality also accompany a mobility limitation (Guralnik et al., 1993; Hardy, Kang, Studenski, & Degenholtz, 2011). Clinical and community barriers can limit healthcare access and quality of care for people with mobility limitations (Krahn et al., 2015). Existing data from population based surveys are constrained in their ability to consistently identify people with mobility limitations and study their health over time (Iezzoni, 2002; Ward, Myers, Wong, & Ravesloot, 2017).

Healthcare administrative data represent an important opportunity for health services and outcomes research to address health disparities experienced by people with mobility limitations. Unfortunately, however, appropriate tools for identifying this population using this new data source do not exist. The population of people with mobility limitations is made up of people with many different health conditions and varying levels of mobility and assistive device use that make identifying this group very challenging (Iezzoni, 2002). The complicated needs and multiple co-morbidities among people with mobility limitations add complexity to this challenge (Gulley, Rasch, & Chan, 2011). Some healthcare administrative data algorithms have been developed for identifying people who have *any* disability (Ben-Shalom & Stapleton, 2016; Davidoff et al., 2013; Faurot et al., 2015), but these tools are too broad to specifically identify people with mobility limitations. No algorithms have been developed to explicitly study a cohort of people with mobility limitations using healthcare administrative data. The lack of a mobility limitation algorithm represents a significant barrier to identifying, monitoring, and studying the health of people with mobility limitation. As the use of healthcare administrative data in research grows, so does the need for such tools to study particular populations. Without these tools, the health disparities gap among people with and without disabilities cannot be addressed. A mobility limitation algorithm is needed for research and evaluation of policy, programmatic, and environmental interventions that specifically target people with mobility limitations.

In this chapter, I present a novel algorithm for identifying and studying people with mobility limitations using healthcare administrative data. My approach is strengthened by the use of many different types of healthcare administrative data available through the United States Department of Veteran's Affairs that have not been previously utilized in existing algorithms for identifying any disability. In what follows, I describe the development of an algorithm that uses a sample of veterans whose healthcare administrative data were linked to self-reported mobility limitation. I report on how well the algorithm performs in predicting a mobility limitation and conclude with a discussion of how the algorithm can be used for future research on healthcare services and health outcomes for people with mobility limitation.

B. Background

1. Limitations of existing sources for studying mobility limitation

Existing sources for researching health services and outcomes for people with mobility limitations are inadequate. Much of the public health research on people with mobility limitations in recent years has come from national surveys, such as the National Health Interview Survey (NHIS), Behavioral Risk Factor Surveillance System (BRFSS), and the American Community Survey (ACS). (Centers for Disease Control and Prevention, 2018a). Most national surveys that include disability identifiers are often only available as cross-sectional samples (Livermore, 2007), which limits the ability to conduct longitudinal research that can help answer important questions, such as how interventions (e.g. improvements to healthcare office compliance with the Americans with Disabilities Act (ADA)) affect people with mobility limitations and whether those with existing mobility limitations are able to maintain their health status. The sample size of people with mobility limitations in many national surveys is often too small and requires pooling of several years of data (C. Carroll et al., 2014). The few longitudinal panel studies that report on mobility limitation are mostly focused on older adults (Livermore, 2007) (e.g. Health and Retirement Study and Medicare Current Beneficiary Survey).

Clinical and community based studies are another source of data for research on mobility limitation, but such data are time and resource intensive to collect. In clinical studies, mobility limitation may be assessed based on physical tests of walking, standing, and/or climbing stairs, but these also vary greatly (Vincent, Vincent, & Lamb, 2010). In studies conducted in community based settings, mobility limitation has been defined through self-reported difficulty walking, or by use of specialized equipment, such as canes, walkers, or wheelchairs (Rimmer, Rauworth, Wang, Heckerling, & Gerber, 2009). Clinical and community based studies also tend to utilize smaller samples and focus on people with specific health conditions (Fok, Henry, & Allen, 2015) limiting the generalizability of their results.

2. The opportunity of healthcare administrative data

Healthcare administrative data offer a new potential source for studying healthcare services and outcomes for specific populations, such as people with mobility limitation. Data from healthcare are routinely collected and stored in large repositories that are maintained by hospitals, healthcare systems, and health insurers. The Veterans Health Administration is the longest running healthcare administrative database (Brown, Lincoln, Groen, & Kolodner, 2003). Healthcare administrative databases contain many different types of information related to healthcare, including reimbursement claims, diagnoses, procedures, medication prescriptions, equipment, and other services. Such databases were originally setup for reimbursement purposes and monitoring of health policies (Gavrielov-Yusim & Friger, 2014).

EHR systems are used by healthcare providers (nurses, doctors, and other health professionals) to develop an electronic record of patient's health. Information is entered on diagnoses, procedures, medications etc. to allow for better monitoring of health over time and across institutions (Gavrielov-Yusim & Friger, 2014; Mazzali & Duca, 2015). The information recorded by providers is then coded with specific coding schemes that are used for billing to insurers.

Common coding systems were developed for healthcare administrative data and are used to standardize data entry. Diagnoses and procedures are often billed for using codes from the International classification of Diseases, Ninth Revision, (ICD-9-CM) as well as the Tenth Revision (ICD-10-CM) starting in 2015. ICD-9-CM codes are maintained by the National Center on Health Statistics and the Centers for Medicare and Medicaid Services (CMS) (National Center for Health Statistics, 2019). Current Procedural Terminology (CPT) codes are another system for procedures and tests developed and maintained by the American Medical Association and used for billing of physician services. Durable medical equipment, supplies and devices used in healthcare settings or provided to patients are coded using the Healthcare Common Procedures Coding System (HCPCS), which is maintained by the Centers for Medicare and Medicaid Services (CMS) (Centers for Medicare and Medicaid Services, 2013). Additional data that come from healthcare include enrollment data, demographic data, data generated for business purposes, and quality improvement related to procurement. These many different types of datasets are stored in data warehouses, where researchers can then access them and use the specific codes (e.g. diagnosis, procedure etc.) to identify cohorts with specific characteristics. I will henceforth refer to these types of data as healthcare administrative data.

Because healthcare administrative data are the product of business processes, when re-purposed for research, an understanding of those data generating processes is important in assessing their suitability, preparation for analysis, and interpretation. While research using these data has grown, only a small percentage of studies evaluate how well the codes they used correctly identified their target population (van Walraven, Bennett, & Forster, 2011). As such, the quality of administrative data has been questioned (Grimes, 2010; Iezzoni, 1997). The largest concern is misclassification of patients and the extent to which that leads to selection bias (Gavrielov-Yusim & Friger, 2014). Analysis using administrative records requires a thorough understanding of 1) how data are collected, 2) who inputs the data, 3) how data are stored, and 4) the reliability of the data (Burgess et al., 2011; Johnson, Kamineni, Fuller, Olmstead, & Wernli, 2014).

There is a need for research studies using healthcare administrative data to evaluate the operational definitions used (Benchimol et al., 2011). For example, a doctor or nurse might record a diagnosis of Parkinson's disease when a patient has come in with symptoms of Parkinson's, but further testing indicates that the patient has another similar condition and not Parkinson's. This scenario illustrates how misclassification could occur using only the record from the first instance of the Parkinson's disease. Researchers develop approaches to address the threat of misclassification using combinations of codes. For instance, related to the Parkinson's scenario, an algorithm by Szumski et al. identifies Parkinson's using at least two encounters with the ICD 9 code 332.0 (Szumski & Cheng, 2009). Similar rules have been developed for other conditions and these combinations of codes are evaluated based on a comparison of the specific codes or groups of codes with a gold standard criterion.

As the availability of healthcare administrative data have increased, there are important opportunities for public health researchers to track and monitor healthcare access and quality, utilization and outcomes (Birkhead et al., 2015; Casey et al., 2016). Some researchers have shown how healthcare administrative data can supplement data from the BRFSS, which is commonly used for State level public health surveillance (Klompas et al., 2017). Healthcare administrative data are increasingly being used to define cohorts with specific characteristics or conditions (Shivade et al., 2013) and can be used to study and monitor people over time, which is not always possible with national health survey data. An important group that could benefit from new research approaches that leverage healthcare administrative data are people with disabilities (Turk & McDermott, 2018). Studies using Medicaid and Medicare claims files to identify individuals with IDD have greatly expanded the hypotheses that can be studied related to healthcare access and outcomes (Xu et al., 2017) and has been part of national funding efforts from the CDC National Center on Birth Defects and Development Disabilities (NCBDDD) (National Center on Birth Defects and Developmental Disabilities, 2019). However, tools to study people with mobility limitation are lacking, although they are the largest subgroup within the population who has a disability.

3. Use of administrative data to identify populations with mobility limitations

The current literature contains many examples of sets of codes for identifying conditions frequently accompanied by mobility limitation, including Spinal Cord Injury (SCI) (Smith et al., 2010), Multiple Sclerosis (MS) (Culpepper, Ehrmantraut, Wallin, Flannery, & Bradham, 2006), Traumatic Brain Injury (TBI) (Bazarian, Veazie, Mookerjee, & Lerner, 2006), Stroke (Tirschwell, Kukull, & Longstreth, 2000), and Osteoarthritis (OA) (Williamson et al., 2014). However, the degree of mobility limitation experienced by individuals with these conditions can range from none to complete (Iezzoni, 2002). Therefore, the presence of one of these health conditions is not a sufficiently specific indicator of mobility limitation. Neither is it a sufficiently sensitive indicator since many individuals with mobility limitation do not carry a diagnosis of any of those conditions (Patla & Shumway-Cook, 1999). An individual with balance problems may need specialized mobility equipment but not have any of these specific health conditions. Use of an assistive mobility device (e.g., a cane, wheelchair) may be another indicator of a mobility limitation. Healthcare claims, benefits management records, or other administrative data containing records of delivery of these devices to individuals are another potential source of information for identifying mobility limitation. However, these devices are often prescribed for temporary conditions (e.g., hip fracture rehabilitation) and it is not always possible to determine from the device itself whether the individual has a chronic, persistent mobility limitation (Iezzoni, 2002). In order to identify and study mobility limitation using healthcare administrative data, an algorithm is needed that can account for the complexity and time-varying nature of mobility limitation. An algorithm is a combination of healthcare administrative data that is used to identify a condition a researcher wishes to study (Mazzali & Duca, 2015).

4. **Deficiencies of current algorithms/code sets for studying mobility limitations**

The codes available in the current literature to study mobility limitation using healthcare administrative data are inadequate. A rigorous evaluation of the codes was not completed in the existing literature or specific attention to the ability of the definition to completely and accurately identify the target population. The Centers for Medicare and Medicaid Services (CMS) Chronic Conditions Data Warehouse (CCW) is a resource for defining cohorts using healthcare administrative data and includes one set of ICD 9/10 diagnosis codes on mobility impairment. (Centers for Medicare and Medicaid Services, March 2015) However, the codes identify only paralytic conditions (paraplegia, quadriplegia, hemiparesis). While individuals with these mobility impairments most often have mobility limitations, for some, it may be very mild and they may not self-report that they have a mobility limitation. More importantly, use of those codes alone is not be helpful in identifying individuals with non-paralytic conditions that have mobility limitation.

Khoury et al. (2013) identified physical disability (mostly mobility) using healthcare administrative data to study the prevalence of chronic diseases among Floridians on Medicaid. The purpose of their article was not to validate an algorithm on mobility limitation, but their study is one of the few examples that used healthcare administrative data to identify mobility related limitation. They focused on two factors—health conditions and assistive devices—to define their cohort. An expert panel of physicians and epidemiologists identified a list of ICD-9 codes representing health conditions associated with physical disability. The expert panel input established some content validity for the set of codes they used. However, the authors did not evaluate the sensitivity/specificity of their operational definition of mobility limitation. In other words, in their approach to using healthcare administrative data, the authors did not compare whether those identified as having a mobility limitation actually have a mobility limitation. Future research using Khoury and colleagues' methods will benefit from being able to use readily available code sets, but will be susceptible to criticism regarding the reliability of the codes in correctly identifying the target population.

Although not specific to mobility, three studies developed claims based algorithms for identifying individuals with difficulties in activities of daily living (ADLs), with one of the activities being walking (Ben-Shalom & Stapleton, 2016; Davidoff et al., 2013; Faurot et al., 2015). In all three studies, the authors used an individual's responses to questions about having limitations in *any* ADLs from the Medicare Current Beneficiary Survey (MCBS) as the gold standard that their model was attempting to predict. The models in each study worked well in predicting any ADL difficulty (Davidoff: C-Statistic = 0.92, Faurot: C-statistic = 0.85 & Ben-Shalom: C-statistic = 0.75). While these studies serve as good models for evaluating functional limitation related algorithms, they are too broad for specifically identifying mobility limitation. Knowing that a population has one of several limitations is not useful for developing targeted strategies, interventions, or policies that are often needed to be effective for those with mobility limitation.

Taken together, the current literature shows the promising opportunity of using healthcare administrative data to identify people with any functional limitations, but also illustrates the limitations of currently available algorithms for specifically identifying people with mobility limitation. The inability to reliably identify mobility limited populations in healthcare administrative data is a significant barrier to realizing the potential of such data to address important research questions aimed at improving this populations' health outcomes (Iezzoni, 2002). Of particular relevance to my dissertation is the fact that the lack of an established mobility limitation algorithm prevents research that utilizes 'big data' to study critical health outcomes, such as obesity.

Healthcare administrative data from the US Department of Veterans Affairs (VA) provide a unique opportunity for studying populations with mobility limitations. Data from the VA include records generated through clinical activities and non-clinical administrative processes, such as dispensing of durable medical equipment (Burgess et al., 2011). The VA has the oldest and most comprehensive electronic source of healthcare administrative data (Brown et al., 2003). In this study, I leverage a large data source developed from VA data warehouses for an NIH R01 study called the Weight and Veterans Environments Study (WAVES). This dataset provides the opportunity to study a large and geographically diverse group of veterans.

Veterans are an important group to study in relation to mobility limitations because veterans often experience injuries linked to their military service. Although the rates of mobility limitation are similar among veterans and non-veterans, at around 13% (Courtney-Long et al., 2015; Holder, 2016), the non-veteran group includes those born with mobility limitations; thus, the veteran group has a larger percentage of acquired mobility limitations, which resulted either through military service or in civilian life. Being able to identify a cohort with mobility limitations opens the door to new studies of existing or new policies that affect the population of people with mobility limitations as a whole. For instance, such cohorts could be studied in relation to new policies or practices on accessible weight scales, which have been identified as a problem in weight management practice in the VA for people spinal cord injuries (Locatelli & LaVela, 2016).

5. **Purpose**

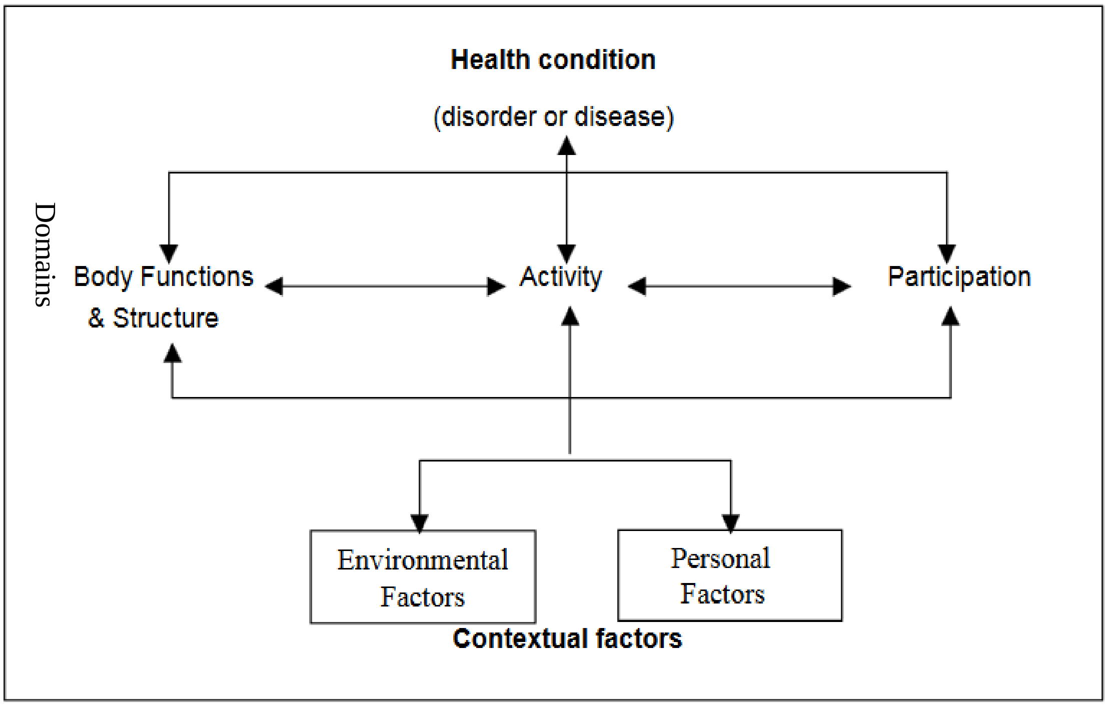
The purpose of this chapter is to develop and evaluate an approach for identifying people with mobility limitation using healthcare administrative data from the VA. I obtained data on self-reported mobility limitation for a sample of veterans who completed the Medicare Current Beneficiary Survey (MCBS) and linked it to healthcare administrative data from the VA. The self-reported mobility limitation serves as the gold standard criterion of having a mobility limitation. I used predictive modeling to predict the self-reported mobility limitation using only the healthcare administrative data. Thus, the central research question is *whether in the absence of self-reported mobility limitation, healthcare administrative data alone can reliably discriminate between those who do and do not have a people with mobility limitation.* Because the severity of mobility limitation can have differential impacts on healthcare access and outcomes, I evaluated multiple approaches to operationalizing mobility limitation. These included binary (yes/no) as well as multi-level mobility limitation definitions. This chapter contributes to the field of public health and disability by introducing a novel tool that provides new research opportunities for studying health services and outcomes for people with mobility limitation. In assessing the quality of the algorithm, I will also identify what factors most strongly predict having mobility limitations. Researchers across multiple disciplines including public health, physical medicine and rehabilitation, occupational therapy, physical therapy, and disability studies as well as hospital systems and health insurers can use the algorithm to identify and monitor the health of individuals with mobility limitations over time.

6. **Conceptual model**

The International Classification of Function, Disability and Health (ICF) is a biopsychosocial model of health and function that serves as a conceptual framework and important tool for studying disability (see Figure 1). The ICF was developed by the World Health Organization (WHO) as a classification of disability and health. The ICF incorporated a social model, which views disability as also created by societal and environmental factors instead of a medical model that characterizes disability as a medical problem (World Health Organization, 2001). In the ICF, human functioning is expressed across three domains of body function/structure, activities, and participation. Individuals can experience limitations in any one of these domains or across multiple domains. Functioning is moderated by environmental, personal factors, and health conditions (World Health Organization, 2001). The arrows in the ICF model are bi-directional to show how the domains, health conditions, and contextual factors can influence each other.

Similar to ICD9 and ICD10 codes, the ICF is also a classification system. Instead of codes for specific diagnosis and procedures, the ICF classifies functioning and disability into specific codes across the domains and factors (World Health Organization, 2001). Mobility is a subdomain within the activity domain. Mobility limitations include difficulty with several physical tasks, including walking, climbing stairs and transferring in various environments (Patla & Shumway-Cook, 1999). The phrase ‘disability’ is not one of the factors in the ICF and so is not the same as mobility limitation. In the ICF, mobility disability is seen as an interaction between the three domains, health conditions, and contextual factors. The ICF has been used to examine empirical relationships between its component factors and health outcomes (Robinson & Butler, 2011) or to develop new conceptual models, such as the model of Physical

Figure 1: The WHO International Classification of Function, Disability, and Health (ICF)* (World Health Organization, 2001)



*Reused with permission from the WHO (see Appendix D)

Activity and Disability (van der Ploeg, van der Beek, van der Woude, & van Mechelen, 2004)

In this chapter, I identified factors available in the VA's healthcare administrative data that the ICF conceptualizes as being associated with mobility limitation. These data fall within the ICF's health conditions, body/function structures, environmental factors, and social factors. I analyzed the degree to which these data predicted a self-reported activity limitation (e.g. mobility). Mobility limitation can range from those with mild limitations who might ambulate with a cane to those with such severe limitation that they are never able to ambulate independently. Shumway-Cook et al. (2005) developed a multi-level operational definition of mobility limitation using the MCBS and based on four survey questions on difficulty walking. They combined responses to these four questions to classify respondents as non-walker, severe limitation, moderate limitation, mild limitation, or no limitation. A multi-level operational definition of mobility limitation is valuable for understanding whether outcomes might differ depending on the severity of the mobility limitation. Significant relationships with particular health outcomes may only exist for those with severe limitations and not those with mild limitation. For instance, results from Van Holle et al. (2016) suggested that the association between the neighborhood environment and physical activity differed by level of mobility limitation. For chapter two of this thesis, a multi-level mobility limitation variable would help in understanding whether an association with BMI exists only for certain levels of mobility limitation. Differentiating between severity levels has not been undertaken in studies that have developed functional limitation algorithms. In this study, I assessed how well a multi-level mobility limitation algorithm performed at differentiating between severity levels. Because correctly classifying the level of mobility limitation may not be possible, I also tested the performance of a binary predicted mobility limitation variable, which is a valuable starting point to facilitate future research using healthcare administrative data to study health outcomes among people with mobility limitations. Binary mobility limitation variables are used in most of the national cross-sectional surveys, such as the BRFSS, NHIS, and NHANES.

C. Methods

1. Data sources

I used several data sources to develop the mobility limitation algorithm. The cohort used in this study came from the WAVES, which included 3.2 million veterans nationwide (Zenk et al., 2018). I utilized data that are housed in the Veteran's Health Administration (VHA) Corporate Data Warehouse (CDW), such as electronic health records and Medicare claims. The data were developed for the years 2009 – 2013 and a look-back period from 2007-2008 captured baseline health. The inclusion criteria for WAVES was having at least one visit to a VA facility in the two years prior to their baseline year. The visit could be for inpatient or outpatient services. The sample included veterans 20-80 years old at baseline. Veterans were excluded who had no encounters for all of the years, had no home address for any of the years, or had a long nursing home stay at baseline (>90 days) (Zenk et al., 2018). I developed new variables on assistive devices using the National Prosthetics Patient Database (NPPD), as well as Medicare administrative and survey data. I used these data to develop independent predictors and the dependent variables on self-reported mobility limitation.

2. **<u>Dependent variable: mobility limitation</u>**

In this chapter, I have utilized the operational definition of mobility limitation laid out by Shumway-Cook et al. (2005). In their approach, mobility limitation is based off four questions on walking difficulty. Although mobility can encompass other dimensions, this definition focuses on walking, which is the activity most people associate with mobility (Shumway-Cook et al., 2005). Shumway-Cook and colleagues explain that their approach to defining mobility limitation is based on a physical test that is given to people in physical rehabilitation, called the Functional Independence Measure (FIM) (Fiedler & Granger, 1996). The "underlying assumption [of the FIM] is that individuals requiring equipment are more restricted than those who do not use equipment but less restricted than those requiring the personal assistance of another" (Shumway-Cook et al., 2005, p. 1218). The FIM and the ICF were found to be very similar in terms of their performance as rehabilitation outcomes (Kohler et al., 2013; Tarvonen-Schroder, Laimi, Kauko, & Saltychev, 2015). The difference is that the FIM is used more often in rehabilitation practice.

I obtained self-reported mobility limitations from the Medicare Current Beneficiary Survey (MCBS) for the years 2010 to 2013 based on years that I had access to veteran's healthcare administrative data. The MCBS is an ongoing survey of Medicare enrollees who participate in a 4-year panel (Adler, 1994; Centers for Medicare and Medicaid Services, 2003). Data were collected through interviews with Medicare Enrollees one to three times a year depending on the year of the panel. There are two releases of the data: *Access to Care* and *Cost and Use*. The two releases contain data for slightly different groups of Medicare enrollees. The Access to Care is the group that is <u>always</u> enrolled and cost and use is the group that is <u>ever</u> enrolled, meaning that some could have been not enrolled for some of the year (Erbland, 2017). I utilized both releases to capture the greatest number of people and surveys available and because both releases include the RIC_2 module (Health Status and Functioning (Community)) that asks about walking difficulty. The RIC_2 module was asked in the fall of each year and module RIC_8 also included the interview date (Centers for Medicare and Medicaid Services, 2003). It was not necessary to use survey weights because my analysis was not concerned with developing weighted population projections.

I linked veterans in the WAVES study to a dataset of all veteran respondents in the MCBS using social security numbers (SSNs). The MCBS sample included veterans that were in the VHA system and took the MCBS. Both datasets had complete records of SSN data. I matched 978 veterans who were in the WAVES sample and also in the MCBS sample for 2010-2013. Fourteen of the veterans ‘refused to answer’ the questions on difficulty walking and were dropped, leaving a total of 964 veterans in the analytic sample.

In Figure 2, I show the four questions that were asked about difficulty walking on the MCBS and the responses among the 964 veterans in the WAVES sample. The first question is “because of a health or physical problem, do you have any difficulty walking?”. Respondents who say yes or that say they are unable to walk for this first question are subsequently asked if they “use special equipment or aids to help you with walking?” and “if they receive help from another person with walking?” Each of these questions was coded as (0) for no or (1) for yes. Unlike in Shumway-Cook et al. (2005), in the MCBS data from 2010-2013, the ‘difficulty walking a quarter mile’ question was on a Likert scale. Respondents were asked if they have “no difficulty at all, a little difficulty, some difficulty, a lot of difficulty, or are not able to walk a quarter mile (2 to 3 blocks)”. I dichotomized the scale so that those with some difficulty (3), a lot of difficulty (4), or unable to walk a quarter mile (5), were coded as a (1) for having a mobility limitation and a little difficulty (2) or no difficulty (1) were coded as a (0).

There were 345 (36%) of the 964 MCBS respondents who reported any walking difficulty or reported that they were unable to walk. Of these, 221 (64%) used specialized equipment for walking and 44 (13%) needed help from another person with walking. There were 463 who responded that they had no difficulty walking a quarter mile, 100 had a little difficulty, 114 had some difficulty, 121 had a lot of difficulty, 164 were unable to do it, and two subjects refused to answer the question. When the quarter mile question was dichotomized, there were 399 (41%) respondents who reported having difficulty walking a quarter mile.

Figure 2: Model for Classifying Mobility Limitation Severity Based Off Questions on the Medicare Current Beneficiary Survey (adapted from Shumway-Cook et al. (2005)

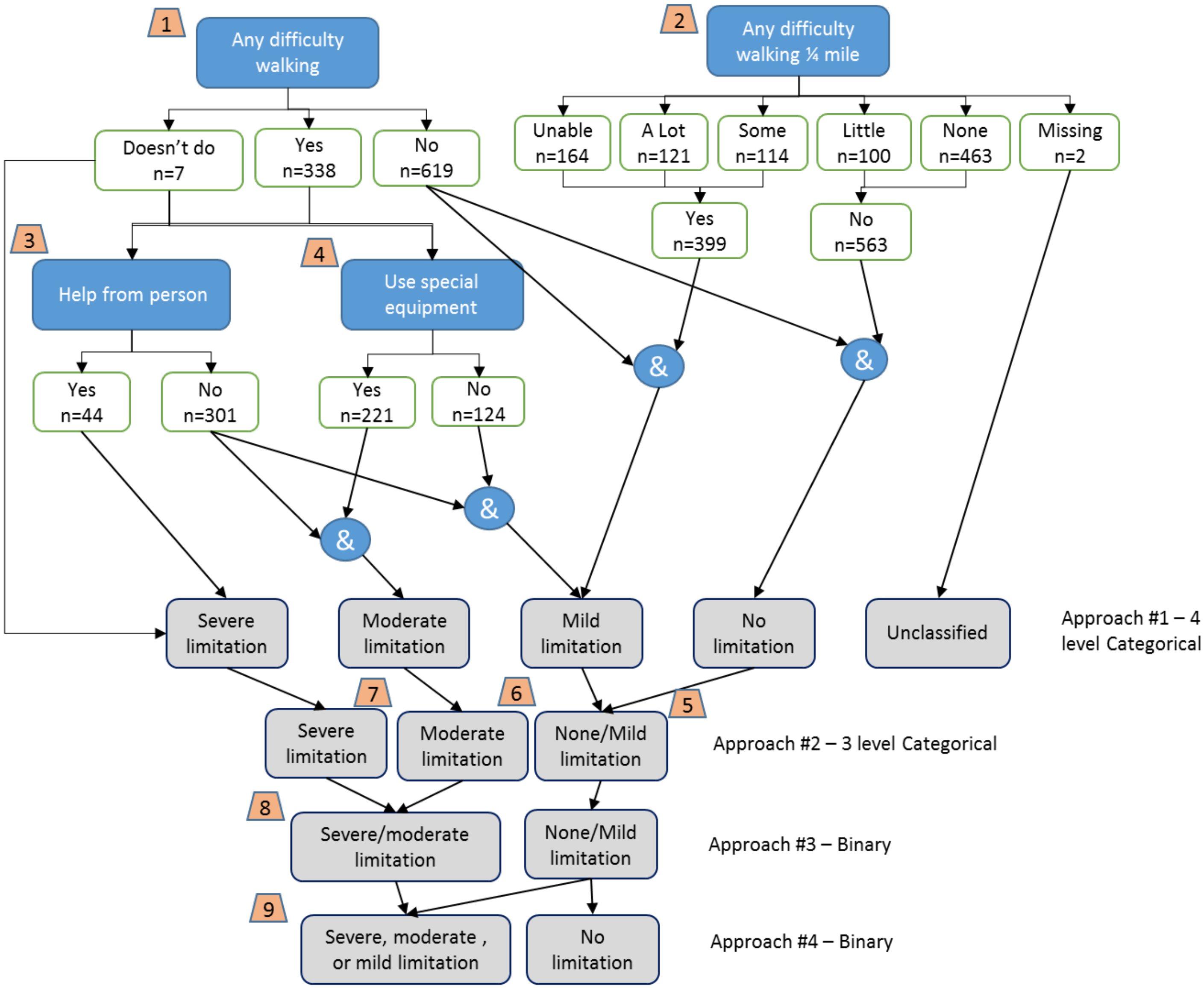


Figure 2: Model for Classifying Mobility Limitation Severity Based Off Questions on the Medicare Current Beneficiary Survey (MCBS) (adapted from Shumway-Cook, Ciol, Yorkston, Hoffman, and Chan (2005) (Continued)

Legend for Figure 2		
MCBS questions (blue rectangles)		
Any difficulty walking		Because of a health or physical problem, do you have any difficulty walking?
Help from person		Do you receive help from another person with walking?
Use special equipment		Do you use special equipment or aids to help you with walking?
Any difficulty walking ¼ mile		Would you say you have no difficulty at all, a little difficulty, some difficulty, a lot of difficulty, or are not able to do it (walk ¼ mile, that is 2-3 blocks)
Approaches to operationalizing mobility limitation (grey rectangles)		
Approach #	Type	Definition
1	Categorical (4-levels)	1. Develop 4 separate logistic regression models (Orange trapezoids 1-4) for each of the 4 MCBS questions 2. Generate predicted probabilities for each question 3. Choose a cut-off to use to create a binary predicted response 4. Combine predicted responses into a 4-level measure – none, mild, moderate, severe. 5. Compare predicted level to the real self-reported answer.
2	Categorical (3-levels)	1. Classify each person as none/mild, moderate, severe 2. Develop 3 separate logistic regression models (Orange trapezoids 5-7) 3. Generate predicted probabilities for each level 4. Z-standardize predicted probabilities 5. Averaged Z-standardized probabilities to classify as predicted none/mild, moderate, severe 6. Compare predicted level to originally classified level of mobility limitation
3	Binary moderate to severe mobility limitation	1. Classify subjects as none/mild or moderate/severe mobility limitation 2. Develop a logistic regression model to predict those with moderate to severe mobility limitations (Orange trapezoid 8) 3. Generate predicted probabilities 4. Choose a cut-off to use to create a binary predicted response 5. Compare predicted moderate-severe limitation to actual moderate-severe limitation
4	Binary mild to severe mobility limitation	1. Classify subjects as none or mild, moderate, and severe mobility limitation 2. Develop a logistic regression model to predict those with mild to severe mobility limitations (Orange trapezoid 9) 3. Generate predicted probabilities 4. Choose a cut-off based to use to create a binary predicted response 5. Compare predicted mild-severe limitation to actual mild-severe limitation

In figure 2, I also show the four different approaches that I used for combining the questions on difficulty walking to operationalize both categorical and binary mobility limitation outcomes based on a similar model from Shumway-Cook et al. (2005). The legend summarizes the steps used for each approach to developing the outcome variables, regression models and how the predicted outcomes would be compared to the actual outcomes.

3. **Predictor variables**

For each of the four approaches to operationalizing mobility limitation, the same set of potential predictor variables were used in developing all of the logistic regression models. Predictors were selected from several of the domains and factors listed in the ICF and which previous literature suggests might be associated with mobility limitation. The description of predictors is organized into environmental factors, personal factors, health conditions, and body functions and structure. No data were available about the participation domain of the ICF. The data sources, reasons for including, and process of coding each predictor variable are described in detail below. The specific classification codes that were used for coding variables on health conditions and assistive devices are listed in Table XXII, Appendix A.

a. **Environmental factors**

i. **Assistive mobility devices**

The National Patient Prosthetics Database (NPPD) was developed by the VHA to keep an accurate record of all prosthetics, medical equipment, and assistive devices, including those related to mobility (Department of Veterans Affairs, 2014). A major goal of the NPPD is to function as a central repository of information on durable medical equipment (DME) and to be able to report quality assurance metrics. The NPPD is managed by the prosthetics service of the VHA and has been in existence since 1997 (Department of Veterans Affairs, 2014). When a healthcare professional determines someone needs a mobility related assistive device, they prescribe the device, and this sends a referral to the prosthetics service, who enters the information into the NPPD. They enter an item that is prescribed and then they choose from a menu of HCPCS codes related to that item (Greg Hageman, NPPD Data Steward, personal communication, January 9, 2018). There is one record for every device, part, and accessory ordered.

Repairs to mobility devices are also recorded in the NPPD. We used data from 2008-2014 so that there are data prior to the first interview as well as after. Records were dropped if they were listed as incomplete. An incomplete record could reflect a situation where a physician submits an order for an assistive mobility device but the device is never picked up by the patient.

The HCPCS codes are organized into groups of related codes called ‘NPPD lines’ (Department of Veterans Affairs, 2014). For instance, there are nine HCPCS codes for different types of manual wheelchairs and these are grouped into an NPPD line called, ‘manual wheelchairs’. The NPPD lines are further grouped into NPPD groups, such as ‘wheelchairs and accessories’ that includes manual wheelchairs, power wheel chairs, scooters and wheelchair accessories. In this way, the 4,330 HCPCS codes are organized into 156 NPPD lines and 16 NPPD groups. These categories are similar to groups developed for Medicare in the Berenson-Eggers Type of Service (BETOS) codes (Research Data Assistance Center, 2018). The NPPD lines and NPPD groups are updated periodically as new HCPCS are developed by the Centers for Medicaid and Medicare Services (CMS) or internally by the VHA (Greg Hageman, NPPD Data Steward, personal communication, January 9, 2018). In Table XXI, Appendix A, I list the NPPD lines and groups.

There are several types of mobility devices that can be identified in the NPPD. Previous research as well as conversations with the prosthetics service suggested using NPPD lines instead of individual HCPCS codes because of the variance in quality of HCPCS code data entry and regional variation in practices by Veterans Integrated Services Networks (VISN). (Hubbard Winkler et al., 2012) I developed initial indicators using a combination of NPPD lines and NPPD groups. One exception where I used individual HCPCS codes was for canes, which were in a broader NPPD group (medical equipment) and did not have their own separate NPPD line. I coded six dummy variables from the NPPD data that again follow similar groupings in the BETOS: 1) ‘artificial leg’ for any prosthetic from foot to whole leg; 2) ‘surgical’ for surgical implants (e.g. in foot, knee, hip etc.); 3) ‘standing mobility’ included cane, walker, and walking aid accessories; 4) ‘orthotics’ included different types of braces and apparatuses that attach to the lower body; 5) ‘seated mobility’ included manual wheelchairs, power wheelchairs and scooter; and

6) ‘immobility’ for items related to home mobility aids and devices, such as a hospital beds, patient lifts and ramps into the home.

The VA has a strong commitment to providing assistive mobility devices to veterans. As such, the benefit for assistive mobility devices is very generous compared to other healthcare systems, such as Medicare (Hubbard Winkler et al., 2010). Some veterans may still choose to receive their mobility devices from a non-VA source for various reasons, such as geographic proximity to a VA facility or preference of healthcare providers. I also coded durable medical equipment data from Medicare to partially account for non-VA sources of assistive mobility devices. I applied the same NPPD line coding system and indicators to the Medicare data and appended it to the NPPD data.

ii. <u>Healthcare utilization</u>

I included variables on inpatient stays, outpatient primary care visits, and specialist visits. A hospital stay may be a sign of a more serious health event that could impact mobility. All the healthcare utilization variables were visit/stay counts. As part of the iterative process described below, I also tested binary and multi-category forms of these variables as well. The healthcare utilization data were obtained from both the VHA and Medicare.

iii. <u>Geography and neighborhood income</u>

Additionally, I included a variable for the census division the veteran resided in. This was included to capture aspects of the environment that potentially affect mobility limitation, such as weather and topography as well as any policy or healthcare related practices that are related to geographic regions and may affect certain treatments related to mobility limitation as is discussed in the Dartmouth Atlas of Health Care (Wennberg, Fisher, Goodman, & Skinner, 2008).

The healthcare administrative data available for this study do not include measures of income or poverty, which are also associated with mobility limitation (Lauer & Houtenville, 2018). To approximate income, we used measures at the census tract level based on the veteran’s home address and included one continuous measure of the percentage below the federal poverty line and another continuous measure on the median household income.

b. <u>Personal factors</u>

I included several demographics obtained from the VHA Corporate Data Warehouse (CDW). These included gender (male, female), race/ethnicity (white, black, Hispanic, other), age (continuous and categorical by ten year age groups), marital status (married, single, widowed) and priority groups. There are nine VHA priority groups and these were split into three groups based on a VHA determination that affects co-payments as no copayment group, some copayment group, and more copayment group. Veterans with a service-connected disability rated 50% or higher and housebound veterans determined to be ‘catastrophically disabled’ are in the no copayment group (US Department of Veterans Affairs Information Resource Center, 2013). Service connected disability cuts across various types of disability beyond mobility, including physical, sensory, cognitive, psychological, etc. All of the demographic variables were categorical measures.

c. <u>Health conditions</u>

There are several diseases and conditions that are associated with having a mobility limitation. After a stroke, some people have a weakened ability to move half their body (hemiparesis). People with osteoarthritis can have pain and stiffness that limits their walking. As a starting point, I used the ICD-9 codes and groups of codes developed by Khoury and colleagues because they provide a comprehensive set of codes that could potentially be related to a mobility limitation. Because of the small sample and low prevalence of many conditions, I used ICD9 code groups instead of individual codes. For instance, I used the code group of disorders of the peripheral nervous system (PNS), which included codes 353-357.9 & 359.0-359.9. I removed code sets that were specific to congenital conditions as veterans only have acquired disabilities. For instance, I removed infantile cerebral palsy codes 343.0-343.9. I supplemented the list by Khoury with some additional diagnoses not on their list but often related to difficulty walking, including stroke, osteoarthritis, and ALS (amyotrophic lateral sclerosis, also called Lou Gehrig’s disease) (Hoenig, Pieper, Zolkewitz, Schenkman, & Branch, 2002; Hubbard Winkler et al., 2010). I added two general diagnoses related to difficulty walking that may be used to diagnose a more general state but not specific to a condition, and these include ‘abnormality of gait’ and ‘difficulty walking’. When available, I used previously validated code sets that showed acceptable levels of sensitivity and specificity for the codes I added. Several of the conditions and equipment I incorporated were also used in the algorithms developed by Davidoff et al. (2013) and Faurot et al. (2015) for having ‘any functional limitation’. Those studies found that a wheelchair and a hospital bed were two of the strongest predictors in those algorithms (Davidoff et al., 2013; Faurot et al., 2015).

Chronic conditions can potentially affect a person’s answer to a question about their walking difficulty. For instance, someone with chronic obstructive pulmonary disease (COPD) has difficulty breathing, which may be a significant reason for answering that they have difficulty walking a quarter mile. As part of WAVES, several chronic health conditions from the Chronic Conditions Warehouse were coded as dummy variables (Zenk et al., 2018). Twenty chronic conditions were included as potential predictors.

To strengthen the validity of ICD9 code sets I used as predictors of mobility limitation, I applied a set of rules. First, a dummy variable for each health condition was developed based on any healthcare encounter record. The dummy variable was only kept on or considered a ‘true’ diagnosis if the diagnosis was inpatient, or if there were two outpatient records for that code that were greater than thirty days apart.

Since high BMI is associated with greater likelihood of having a mobility limitation, I included a variable for the individual’s BMI in that year and also coded an indicator variable for morbidly obese (BMI≥ 40). Weight was measured as part of any clinical or inpatient visits and was obtained from patient level encounters. An annual weight measure was calculated by using the mean weight for a year and, when available, mean weights for the second half of the year to serve as outcome measures in WAVES (Zenk et al., 2018).

d. <u>**Body functions and structure**</u>

Certain surgeries and procedures may affect mobility limitation. I included having an amputation, knee replacement, and hip replacement as potential predictors. I also included a code group for paralytic conditions, such as paraplegia, quadriplegia, hemiplegia, and hemiparesis.

4. **<u>Development of the analytic dataset</u>**

The BMI and morbid obesity variable as well as variables concerning demographic, healthcare utilization, geography, and neighborhood income were developed at the person-year level and were joined to each corresponding year of the MCBS. There were 1,913 person-year observations for the 964 veterans who took the MCBS. There were 40 of 1,913 observations that had missing data for some of the person-year variables because they had not yet entered the WAVES study cohort but had an MCBS response. I selected the first year of data for which the person did not have any missing data. For 16 of the veterans, all years where I had an MCBS survey response had missing data on BMI, demographics, healthcare utilization, census division, and census tract poverty. For these 16, I imputed the values for those observations based on the subsequent year's VA data or the average in the case of healthcare utilization variables because they vary over time. Five subjects had no available weight data to impute from and so had missing values for weight related measures.

An operational definition of mobility limitation using healthcare administrative data requires us to set up a window of time whereby diagnoses made in that window are considered potential predictors of the self-reported mobility limitation. The time window is based off a period before and after the specific interview date. Based on each interview date, dummy variables for each health condition or assistive mobility device were coded (1) if the date of diagnosis or receipt of device was within two years of the interview date or 6 months afterwards. In sensitivity analysis, I also tested how a shorter time window in the period before the interview date (1-year instead of 2-years) affected the results. Achieving the right window was challenging. On the one hand, a shorter time window included diagnoses that are more closely related to an individual's responses to walking difficulty, and which may also have helped in excluding diagnoses that had been a problem but were now no longer a problem. For instance, if a musculoskeletal condition was diagnosed and then a new medication was started or rehabilitation helped with the issue, a respondent would not report walking difficulty because of this new treatment. On the other hand, a longer time window is beneficial for dealing with the fact that healthcare administrative data are only available for the dates when a veteran used a health service. A diagnosis may appear in the data two years prior to the MCBS interview, but then not appear only because the veteran did not go to the doctor, or did not go the VA or use Medicare and instead went to a non-VA physician through private insurance. This is somewhat less likely given that the whole sample is Medicare enrollees. So, there is less of a concern about missing data. Lastly, a diagnosis associated with mobility limitation may not appear simply because the veteran did not go to the doctor for that purpose but for other purposes, such as a flu or digestive problem. To control for the timing of diagnosis, I also included a continuous variable for the days between the interview date and the nearest diagnosis date. I log transformed the variable to normalize the data. This variable helps to adjust for diagnoses that occurred a longer time from the interview date.

5. **Statistical analysis**

I calculated the frequency and percentages for each predictor variable. I computed these for the longer time window (two-years before the interview date and one-year after) and the shorter time window (one-year time before the interview data and three-months after). I examined bivariate correlations between each predictor and the outcome variable using Pearson's chi-squared correlation. Some health conditions were combined because of low frequencies (under ten). Variables were only combined if it made conceptual sense, such as three different types of cancers. I began with 53 variables. I grouped similar variables, such as diabetes with and without complications. After grouping or removing those with low prevalence such as sarcopenia and aids, there were 47 candidate predictors. I examined collinearity between predictor variables and removed one variable from a pair if there was a correlation coefficient above 3.0 and they were theoretically very similar. I removed two codes. One was surgical implants from the durable medical equipment data, which was highly collinear with joint replacement procedure codes, and the other was substance abuse disorder, which was highly collinear with liver disease.

I used an iterative process to develop each of the nine multivariate logistic regression models labeled in figure 2. These included four models for each MCBS question in approach #1, three models for each severity level in approach #2, one model for the moderate-severe binary outcome in approach #3, and one model for the mild-severe binary outcome in approach #4. I ran separate models but used a similar four-stage process described below for each model.

In stage one, I used stepwise backwards logistic regression to identify the variables that strongly predicted each outcome by retaining only variables with a p-value of <0.05. This was necessary in order to have confidence in the coefficients obtained in the final models because those are used to estimate the predicted probabilities in other datasets (Benchimol et al., 2011). A similar approach was used for the 'any difficulty' algorithms developed by Davidoff et al. (2013) and Faurot et al. (2015). The backwards stepwise approach removes variables one at a time in order of least significance. Repeatedly, this model attempts to place the most significant excluded terms back in the model, and if it is significant at the $p<0.05$ level then it is kept, otherwise it is removed again (StataCorp, 2017).

The logistic regression model is estimated as:

(1) $P(\textit{mobilitylimitation}=1 \mid x) = G\,(\beta_0 + \beta_1 \textit{environmentalfactors} + \beta_2 \textit{personalfactors} + \beta_3 \textit{healthconditions} + \beta_4 \textit{bodyfunctionsandstructure})$

In equation (1) we examine the probability of *mobilitylimitation*, a binary response variable for the given x's and G is a function that can take on values between 0-1 ($0<G(z)<1$), for all real numbers z (Wooldridge, 2015). β_0 is the constant and β_1 *environmentalfactors* is a vector of the variables related to environmental factors, including assistive mobility devices: prosthetic or orthotics, surgical implants, standing mobility devices, wheelchairs, home mobility aids and devices, healthcare utilization: hospital stays, specialist visits, and primary care visits, and neighborhood income variables: percentage in poverty and median household income; β_2 *personalfactors* is a vector of the demographic covariates: age, marital status, copayment group, race/ethnicity, and gender; β_3*healthconditions* is a vector of the health condition variables : osteoarthritis, asthma, heart failure, diseases of the central nervous system, chronic obstructive pulmonary disease, cerebrovascular disease, depression, difficulty walking or abnormal gait, injuries and joint replacements, diseases of the musculoskeletal system and connective tissue, osteoporosis, peripheral vascular disease, disorders of the peripheral nervous system, renal disease, cancer, diabetes without complications, diabetes with complications, diabetes with OR without complications, liver disease, BMI, and morbid obesity dummy variable; β_4*bodyfunctionsandstructure* is a vector for variables on body functions and structure: amputations, knee replacement, hip replacement, and paralytic conditions.

In stage two, I started with the variables kept in the backwards elimination process and tested whether adding different forms of variables that were removed in the backwards stepwise regression models resulted in any new significant predictors that could be kept. I focused on testing new forms variables that were significant in bivariate correlations. For instance, I tested a categorical form of a continuous measure or a binary form of a categorical measure. If the new variable I added was significant at the $p<0.05$ level, it was retained. In stage three, I tested the inclusion of interaction terms with age, standing mobility devices, seated mobility devices and race because there were theoretical reasons that the interaction of these variables with others may result in a greater likelihood of reporting walking difficulty. An interaction term was retained if both the interaction term and main effect terms were significant. I did not find any significant interaction terms to retain. In stage four, I used a bootstrap procedure to test the consistency of the statistical significance of variables. In this procedure, the software takes random samples of the data with replacement and repeats runs of the models for as many times as specified. The software then calculates a bootstrapped model statistic that the user specifies. I used 200 repetitions and choose to bootstrap the standard errors, which affects the z-statistic and the resulting p-values, helping to strengthen our confidence that the variables kept were significant predictors.

For each model, I calculated the Area Under the Curve (AUC) and its 95% confidence interval. The AUC, also called the C-statistic, is a measure of the goodness of fit of the model and is used to evaluate model performance in logistic regression models similar to the R^2 used in linear models (Hanley & McNeil, 1982). Here, the value is related to how well the model discriminates between 0 and 1, or in this case, having a mobility limitation vs. none. The curve is in reference to the receiver operator curves or ROC, which is a graphical plot of the range of predicted probabilities for the sample. The vertical axis is the sensitivity of the model and the horizontal axis is 1-the specificity, or the true positive rate by the false positive rate respectively (Streiner & Cairney, 2007). A diagonal line represents an AUC of .50, which is the area of a 1x1 square cut in half and represents a model that is as good as random chance at discriminating between those with and without a condition (in this case, mobility limitation) (Streiner & Cairney, 2007). The higher the AUC, the more area is under the receiver operator curve and the better the model is at minimizing false positives and maximizing true positives. An AUC of 0.70-0.79 is considered acceptable, 0.80 – 0.89 is good and 0.90 or above is excellent (Streiner & Cairney, 2007).

In the fifth and final stage, I removed each of the variables retained in the model one at a time to see if this resulted in a lower Bayesian Information Criterion (BIC) without loss of the AUC. Choosing the model with the lowest BIC is done to prevent 'over-fitting' of models (Hurvich & Tsai, 1989). I chose the model with the highest AUC and lowest BIC favoring a higher AUC in cases where both performance statistics changed.

6. **Model evaluation**

After running the models, I generated predicted probabilities of having each outcome. To evaluate the model's predictive performance, it is necessary to establish a cut-off or threshold by which values above that threshold are considered to be a yes for that outcome and everything below that threshold is considered a no. I used Youden's index J to choose the cut-off value. Youden's J is calculated to maximize the sum of the sensitivity and specificity and graphically works out to be the greatest distance from the diagonal line (AUC =0.50) to the ROC curve (Youden, 1950). Based on the cut-offs, I generated new binary variables corresponding to each outcome used for the four approaches I examined. Comparing the self-reported outcomes to the predicted outcomes, I calculated the sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), likelihood ratio positive, likelihood ratio negative, and percentage correct. (See Table I for an explanation of each of these model performance properties.) These measures were all done on the development sample, as I did not have a large enough N for a development and validation sample.For the multilevel measures comparison, the self-reported vs. actual mobility limitation comparison was slightly different. For the four level measure, after creating a predicted binary variable based on the cut-off for each question, I combined the questions using the approach described by Figure 2

TABLE I: DEFINITIONS OF PERFORMANCE PROPERTIES USED FOR REGRESSION MODELS FOR PREDICTING SELF-REPORTED MOBILITY LIMITATION STATUS.

Model performance property	**Definition**
Sensitivity	The proportion of observations that were correctly classified by the model as having the condition
Specificity	The proportion of observations that were correctly classified by the model as not having the condition
Positive Predictive Value	Among those predicted to have a condition, the % that actually have it
Negative Predictive Value	Among those predicted to not have a condition, the % that actually do not have it
Likelihood Ratio Positive	The probability of a positive test result in those with the disease/probability of positive test result in those without the disease or (sensitivity/1-specificity)
Likelihood Ratio Negative	The probability of a negative test result in those with the disease/probability of negative test result in those without the disease or (1-sensitivity/specificity)
Percentage Correct	The proportion of those correctly predicted to have and not have a mobility limitation out of the total sample

and then compared the predicted mobility limitation category to the self-reported mobility limitation category. In the three level measure, I first put each respondent into a mobility limitation category based on Figure 2, and then developed models to predict that category. In this approach, people could potentially be in multiple categories (i.e. predicted to have both a moderate limitation and a severe limitation). As such, I had to devise a strategy for classifying respondents into one predictive mobility limitation category. I z-standardized the predicted probabilities for each level and then took the average across the z-standardized scores. Tertiles of these average scores did not match up well to the actual values. Instead, I manually created two cut-offs to separate the three levels by examining histograms of the average values to identify natural groupings. I also computed the mean and standard deviation of the averaged z-standardized score for each of the self-reported mobility limitation levels. I choose cut-offs that best aligned with the mean and standard deviation of each level but that minimized overlap with the other levels.

7. **Sensitivity analysis**

In addition to testing four alternate mobility limitation outcomes, I also conducted three separate sensitivity analyses. First, I used a shorter time window around the MCBS interview date (12 months prior and three months post interview) instead of the two year window in the period before the interview and the six months after the interview for the binary mild to severe model. To examine the generalizability of the algorithm, I examined an alternate model with only variables that are more likely to be readily available in healthcare claims data outside the VA. In this model, I removed marital status, race/ethnicity, copayment group status, and BMI. I tested how including a variable for the length of time between the interview date and the nearest diagnosis affected the results.

D. **Results**

In Table II I assembled the frequencies and number of cases for each predictor variable. Given that this is a Medicare population, the average age was 70 and most subjects were in the range of 65-79. The sample was mostly white non-Hispanic (73%), almost completely male (96%) and most were married (65%). Approximately 1/3 of the sample was in VHA no copayment group, indicating the highest need and requiring the least copayment for VA health services. Among assistive devices used in the sample, the largest category was canes and walkers (13%) and the lowest was home modifications (5%), which relates to there being more people with mild mobility limitations vs. more severe mobility limitations that require home modifications. The most common type of mobility related health condition was disorders of the Musculoskeletal system (36%) followed by diabetes (35%). Thirty-two percent of the sample had four or more visits with a specialist, 26% had 1-3 visits, and 42% had no visits. A majority of the sample was

TABLE II: CHARACTERISTICS OF VETERANS WHO WERE IN THE WAVES STUDY AND TOOK THE MEDICARE CURRENT BENEFICIARY SURVEY, STRATIFIED BY DIFFERENT SIZED TIME WINDOWS AROUND THE INTERVIEW DATE

	Two-year window[a]		**One-year window[b]**			
Variable	**Mean/ freq.**	**n**	**Mean / freq.**	**n**	**Difference in 2 vs. 1 year window (n)**	**% identified in 2-year and not in 1-year**
Total		964		964		
Demographics						
Age	70					
Age 26-64	23	220				
Age 65-79	61	585				
Age 80-85	16	159				
Male	96	925				
Married (compared to other non-married categories)	65	624				
Non-Hispanic white (compared to other race/ethnicities)	73	701				
No VHA copayment group	29	284				
Some VHA copayment group	40	385				
More VHA copayment group	30	295				
Assistive devices						
Home modifications (lift, standing frame, hospital bed)	5	46	3	27	19	41
Prosthetics or orthotics	8	79	6	54	25	32
Wheelchairs (manual and electric)	7	64	4	42	22	34
Canes, walkers, forearm crutches	13	125	8	77	48	38
Health conditions						
Osteoarthritis	17	160	9	87	73	46
Asthma	3	26	1	12	14	54
Heart failure	5	50	3	32	18	36
Diseases of the central nervous system	7	66	5	45	21	32
Chronic obstructive pulmonary disease	--	--	--	--	--	50
Cerebrovascular disease	5	52	4	34	18	35
Depression	17	168	12	119	49	29
Difficulty walking or abnormal gait	6	60	4	39	21	35
Injuries and joint replacements	4	39	2	21	18	46
Diseases of the musculoskeletal system and connective tissue	36	347	24	234	113	33
Osteoporosis	--	--	--	--	11	65
Peripheral vascular disease	7	71	4	40	31	44
Disorders of the peripheral nervous system	11	103	7	63	40	39

TABLE II: CHARACTERISTICS OF VETERANS WHO WERE IN THE WAVES STUDY AND TOOK THE MEDICARE CURRENT BENEFICIARY SURVEY, STRATIFIED BY DIFFERENT SIZED TIME WINDOWS AROUND THE INTERVIEW DATE (CONTINUED)

	Two-year window[a]		**One-year window[b]**			
Variable	**Mean/ freq.**	**n**	**Mean / freq.**	**n**	**Difference in 2 vs. 1 year window (n)**	**% identified in 2-year and not in 1-year**
Renal disease	11	108	7	65	43	40
Cancer	13	130	10	92	38	29
Diabetes without complications	33	319	25	239	80	25
Diabetes with complications	9	86	7	63	23	27
Diabetes with OR without complications	35	334	26	255	79	24
Liver disease	4	34	2	22	12	35
Paralysis, hemiplegia, hemiparesis	2	23	1	14	9	39
Morbid obesity	6	62				
Healthcare utilization						
Inpatient hospital stay	5	49				
0 or more visits to a specialist	42	404				
1 -3 visits to a specialist	26	254				
4 or more visits to a specialist	32	306				
Census tract measures						
Metropolitan County	73	706				
Percent of census tract below poverty	15					
Median household income (census tract)	$51,433					
Census division						
New England	3	26				
Middle Atlantic	12	114				
East North Central	16	155				
West North Central	11	105				
South Atlantic	25	237				
East South Central	9	85				
West South Central	10	92				
Mountain	8	80				
Pacific	7	69				
Census Division Missing	--	--				
			average % across predictors			38%

[a]Two year time window is two years before the interview date and six months after.

[b]One year time window is one year before the interview date and three months after.

-- Indicates that there is too few subjects and results are not shown for privacy regulations from the VHA.

window vs. 87 in the one-year window. Thus, 73 or 46% of the original 160 were not identified in the one-year window. The difference in diagnoses ranged from 24% for those with diabetes (with and without complications) to 65% for those with osteoporosis. These differences directly relate to the condition and how often patients see a physician for healthcare for that diagnosis. In other words, a diabetic patient sees their physician more frequently than someone with osteoporosis.

In Table III, I show the bivariate correlations between each predictor and the ‘any difficulty walking’ MCBS question. Age was inversely correlated with ‘any difficulty walking’ ($p<0.001$) as those with younger ages were more likely to say they had any difficulty walking. Since the sample is Medicare enrollees, those under 65 reflect people who have disabilities, some of which are mobility limitations. The no VHA copayment group was correlated with difficulty walking ($p<0.001$). All of the assistive mobility device types were highly correlated with any difficulty walking($p<0.001$). Many of the health conditions were correlated with having any walking difficulty. Although many people who have had a stroke have mobility limitation, cerebrovascular disease (CVD) was not associated with having any difficulty walking. As might be expected, having more specialist visits ($p<0.001$), a hospital stay ($p<0.001$), and being morbidly obese ($p<0.001$) were also correlated with any walking difficulty.

In Table IV, I show the coefficients and significance levels for variables kept in models in each of the nine final logistic regression models developed across the four approaches used to operationalize mobility limitation. Having home modifications was the most common significant predictor in all models except for the model predicting use of specialized equipment of walking. Prosthetics and orthotics as well as wheelchairs were predictors for most models except for needing help from another person or the ‘severe’ category in the 3-level measure. Diseases of the central nervous system and diseases of the musculoskeletal system and connective tissue were kept as predictors in many of the models. Being in the no VHA copayment group compared to the other two copayment groups was a significant predictor in several models. COPD, depression, a diagnosis of difficulty walking or abnormal gait, peripheral vascular disease, disorders of the peripheral nervous system, and diabetes were the some of the health conditions kept as significant predictors in a few of the models. Having liver disease, and being quadriplegic or

TABLE III: BIVARIATE CORRELATIONS OF POTENTIAL PREDICTORS WITH REPORTING ANY DIFFICULTY WALKING AMONG VETERANS WHO COMPLETED THE MEDICARE CURRENT BENEFICIARY SURVEY, 2010-2013

Factor	**No walking difficulty**[a]	**Yes walking difficulty**	**p-value**[b]
N	619	345	
Age 26-64	95 (15.3%)	125 (36.2%)	<0.001
Age 65-79	418 (67.5%)	167 (48.4%)	
Age 80-85	106 (17.1%)	53 (15.4%)	
Age, median (interquartile range)	73.0 (67.0, 78.0)	68.0 (63.0, 78.0)	<0.001
Married (compared to other non-married categories)	405 (65.4%)	219 (63.5%)	0.54
Non-Hispanic white (compared to other race/ethnicities)	453 (73.2%)	248 (71.9%)	0.66
VHA copayment group 1	139 (22.5%)	145 (42.0%)	<0.001
VHA copayment group 2	253 (40.9%)	132 (38.3%)	
VHA copayment group 3	227 (36.7%)	68 (19.7%)	
Home modifications (lift, standing frame, hospital bed)	--	39 (11.3%)	<0.001
Prosthetics or orthotics	22 (3.6%)	57 (16.5%)	<0.001
Wheelchairs (manual and electric)	15 (2.4%)	49 (14.2%)	<0.001
Canes, forearm crutches	22 (3.6%)	39 (11.3%)	<0.001
Walker	33 (5.3%)	47 (13.6%)	<0.001
Arthritis	85 (13.7%)	75 (21.7%)	0.001
Asthma	14 (2.3%)	12 (3.5%)	0.26
Heart failure	19 (3.1%)	31 (9.0%)	<0.001
Diseases of the central nervous system	20 (3.2%)	46 (13.3%)	<0.001
Chronic obstructive pulmonary disease	--	14 (4.1%)	0.001
Cerebrovascular disease	26 (4.2%)	26 (7.5%)	0.028
Depression	74 (12.0%)	94 (27.2%)	<0.001
Dementia	13 (2.1%)	--	0.61
Difficulty walking or abnormal gait	17 (2.7%)	43 (12.5%)	<0.001
Injuries and joint replacements	18 (2.9%)	21 (6.1%)	0.016
Diseases of the musculoskeletal system and connective tissue	171 (27.6%)	176 (51.0%)	<0.001
Osteoporosis	--	--	0.64
Peripheral vascular disease	36 (5.8%)	35 (10.1%)	0.014
Disorders of the peripheral nervous system	41 (6.6%)	62 (18.0%)	<0.001
Renal disease	56 (9.0%)	52 (15.1%)	0.004
Substance abuse	36 (5.8%)	23 (6.7%)	0.60
Cancer grouped	93 (15.0%)	37 (10.7%)	0.061
Diabetes without complications	187 (30.2%)	132 (38.3%)	0.011

TABLE III: BIVARIATE CORRELATIONS OF POTENTIAL PREDICTORS WITH REPORTING ANY DIFFICULTY WALKING AMONG VETERANS WHO COMPLETED THE MEDICARE CURRENT BENEFICIARY SURVEY, 2010-2013 (CONTINUED)

Factor	**No walking difficulty**[a]	**Yes walking difficulty**	**p-value**[b]
Diabetes with complications	39 (6.3%)	47 (13.6%)	<0.001
Diabetes with OR without complications	192 (31.0%)	142 (41.2%)	0.002
Liver disease	13 (2.1%)	--	0.82
Morbid obesity	23 (3.7%)	39 (11.3%)	<0.001
Inpatient hospital stay (>0)	20 (3.2%)	29 (8.4%)	<0.001
0 visits to a specialist	294 (47.5%)	110 (31.9%)	<0.001
1-3 visits to a specialist	162 (26.2%)	92 (26.7%)	
4 or more visits to a specialist	163 (26.3%)	143 (41.4%)	
Census Divisions:			
New England	20 (3.2%)	--	0.020
Middle Atlantic	78 (12.6%)	36 (10.4%)	
East North Central	107 (17.3%)	48 (13.9%)	
West North Central	62 (10.0%)	43 (12.5%)	
South Atlantic	160 (25.8%)	77 (22.3%)	
East South Central	54 (8.7%)	31 (9.0%)	
West South Central	43 (6.9%)	49 (14.2%)	
Mountain	49 (7.9%)	31 (9.0%)	
Pacific	45 (7.3%)	24 (7.0%)	
Census Division Missing	--	--	
Metropolitan County	465 (75.1%)	241 (69.9%)	0.077
percent of census tract below poverty	12.2 (6.7, 19.2)	12.8 (7.6, 20.4)	0.17
median household income (census tract)	$48,250 (37,404, 63,424)	46,135 (36,275, 60,169)	0.094

[a] The interview question on walking difficulty in the Medicare Current Beneficiary Survey was "Because of a health or physical problem, do you have any difficulty walking?"

[b] Significance of correlations was assessed for continuous variables using Wilcoxon rank-sum (2 groups) or Kruskal-Wallis (>2 groups) test, and using Pearson's chi-squared test for binary and categorical variables.

-- Indicates that there is too few subjects and results are not shown for privacy regulations from the VHA

TABLE IV: COMPARISON OF COEFFICIENTS RETAINED IN FINAL LOGISTIC REGRESSION MODELS ACROSS THE FOUR APPROACHES TO OPERATIONALIZING MOBILITY LIMITATION USING HEALTHCARE ADMINISTRATIVE DATA AMONG VETERANS IN THE WAVES STUDY WHO COMPLETED THE MEDICARE CURRENT BENEFICIARY SURVEY, 2010-2013

Model number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Approach [a]	**#1**				**#2**			**#3**	**#4**
Variable	**Any walking difficulty**	**Difficulty walking 1/4 mile**	**Uses equipment**	**Needs help from another person**	**None/ mild mobility limitation**	**Moderate mobility limitation**	**Severe mobility limitation**	**Moderate to severe mobility limitation**	**Mild to severe mobility limitation**
Married (compared all other non-married categories)				0.89*			0.86*		
No VHA copayment group (compared to some and many)		0.61**			-.64***			0.47*	0.36*
Some VHA copayment group									
More VHA copayment group (compared to none and some)						-0.59***			
Home modifications (lift, standing frame, hospital bed)	1.66***	2.65***		2.12***	-2.31***	0.85*	2.13***	1.26*	3.15***
Prosthetics or orthotics	1.36***	1.14**	1.20**		-1.35***	1.27***		1.39***	1.48***
Wheelchairs (manual and electric)	1.03*	1.76***	1.37**		-1.25**			1.22**	2.00**
Canes, walkers, forearm crutches			1.40***		-0.65**			0.75**	
Osteoarthritis								0.64**	
Heart failure					-1.05*	0.97**		0.88*	
Diseases of the central nervous system	1.01*	1.53***		1.20*	-1.3***	0.78**	1.13*		1.27**
Chronic obstructive pulmonary disease (COPD)		1.71*							2.39**

TABLE IV: COMPARISON OF COEFFICIENTS RETAINED IN FINAL LOGISTIC REGRESSION MODELS ACROSS THE FOUR APPROACHES TO OPERATIONALIZING MOBILITY LIMITATION USING HEALTHCARE ADMINISTRATIVE DATA AMONG VETERANS IN THE WAVES STUDY WHO COMPLETED THE MEDICARE CURRENT BENEFICIARY SURVEY, 2010-2013 (CONTINUED)

Model number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Approach [a]	**#1**				**#2**			**#3**	**#4**
Variable	**Any walking difficulty**	**Difficulty walking 1/4 mile**	**Uses equipment**	**Needs help from another person**	**None/ mild mobility limitation**	**Moderate mobility limitation**	**Severe mobility limitation**	**Moderate to severe mobility limitation**	**Mild to severe mobility limitation**
Depression	0.71**	0.93*					0.90*		0.72***
Difficulty walking or abnormal gait	0.99*								1.08*
Diseases of the musculoskeletal system and connective tissue	0.73***	0.72***		0.91*	-0.68***	0.51***	0.91**	0.52**	0.60***
Peripheral vascular disease (PVD)		0.91**							0.95**
Disorders of the peripheral nervous system			1.08*	1.10**		0.98***	1.17**	0.81**	
Cancer	-0.58*								
Diabetes with complications									0.65*
Both types of diabetes		0.44**							
liver disease				1.56*			1.56*		
Quadriplegia and paraplegia							1.49*		
Morbid obesity	1.07**	1.73***							
BMI					-0.08***	0.08***		0.04**	0.08***
2 or more visits to a specialist	0.41*								
Percent of census tract below poverty			0.61*			0.02**			
Median household income (census tract)					0.13***				

TABLE IV: COMPARISON OF COEFFICIENTS RETAINED IN FINAL LOGISTIC REGRESSION MODELS ACROSS THE FOUR APPROACHES TO OPERATIONALIZING MOBILITY LIMITATION USING HEALTHCARE ADMINISTRATIVE DATA AMONG VETERANS IN THE WAVES STUDY WHO COMPLETED THE MEDICARE CURRENT BENEFICIARY SURVEY, 2010-2013 (CONTINUED)

Model number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Approach [a]	**#1**				**#2**			**#3**	**#4**
Variable	**Any walking difficulty**	**Difficulty walking 1/4 mile**	**Uses equipment**	**Needs help from another person**	**None/ mild mobility limitation**	**Moderate mobility limitation**	**Severe mobility limitation**	**Moderate to severe mobility limitation**	**Mild to severe mobility limitation**
Census division									
New England									
Middle Atlantic (compared to all other divisions)				1.44**			1.45***		
East North Central									
West North Central									
South Atlantic									
East South Central									
West South Central (compared to all other divisions)	0.79**	0.68*			-0.66*	0.63**			0.82***
Mountain									
Pacific									
Missing									

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

[a] See figure 2 for full descriptions of each of the four approaches to operationalizing mobility limitation, and the 9 regression model outcomes developed.

paraplegic were kept as predictors for models reflecting more severe mobility limitation (needs help from another person and the ‘a lot’ category of the mobility limitation approach. Being from the West South Central census division was a predictor in several models. Cancer was retained for one of the models but was negative. Osteoarthritis and heart failure were health conditions kept in the final, binary, moderate-severe model. In the three level categorical outcome, for the ‘none-model’, the coefficients are similar to the models of individual MCBS questions but are all negative. The only exception to that is census tract median income, which has a positive coefficient of 0.13 ($p<0.001$).

1. **Model performance results**

In Table V the model performance properties are summarized. The AUC value, its standard errors, and 95% confidence intervals are listed for each outcome along with the sensitivity and specificity, the likelihood ratio positive, likelihood ratio negative, positivity predictive value, negative predictive value and the % correct. Overall, the AUC values were considered acceptable (>0.7) and some were close to or above 0.8. The highest AUC was for the severe category of the 3-level outcome. The binary moderate to severe outcome had the highest sensitivity (71%) and needing help from another person had the highest specificity (85%). The highest likelihood ratio positive was needing help from another person (4.51). However, the positive predictive value for needs help from another person was quite low (18%) and indicates that using the algorithm could incorrectly predict people having a mobility limitation who actually do not. Using specialized equipment had the highest positive predictive value at 83%, so that those that are predicted to use specialized equipment will be correct 83% of the time.

In Table VI and Table VII, I compare the % correct of 4-level categorical outcomes and 3-level categorical outcomes respectively. Using the four difficulty walking questions to classify respondents into four levels of mobility limitation, 492 were predicted to have no mobility limitation, 211 had a mild limitation, 111 had a moderate limitation, and 149 had a severe limitation. The predicted 4-level outcome did not match up well to the actual 4-level reported by respondents. The percentage of those who were predicted to have no limitation was correct for 75% of those reporting no limitation, but the percentage correct for the other levels were all below 50%. In the 3-level outcome, it was a similar pattern, as 80% of

TABLE V: COMPARISON OF MODEL PERFORMANCE OF FINAL LOGISTIC REGRESSION MODELS ACROSS THE FOUR APPROACHES TO OPERATIONALIZING MOBILITY LIMITATION USING HEALTHCARE ADMINISTRATIVE DATA AMONG VETERANS IN THE WAVES STUDY WHO COMPLETED THE MEDICARE CURRENT BENEFICIARY SURVEY BETWEEN 2010-2013

Approach[a]	**Category**	**AUC (SE) and CI**	**Sensitivity**	**Specificity**	**PPV**	**NPV**	**LR+**	**LR-**	**%correct overall**
Categorical (4-levels)	Any walking difficulty	0.772 (0.016) CI: (0.740- 0.803)	71%	72%	59%	82%	2.58	0.40	72%
	Difficulty walking ¼ mile	0.779 (0.015) CI: (0.750- 0.809)	66%	79%	69%	77%	3.14	0.43	73%
	Uses specialized equipment	0.734 (0.026) CI:(0.683- 0.784)	61%	78%	83%	53%	2.78	0.50	67%
	Needs help from a person to walk	0.817 (0.036) CI: (0.746-0.888)	68%	85%	18%	98%	4.51	0.37	84%
Categorical 3-levels	None/mild	0.794 (0.016) CI: 0.764- 0.824)	n/a	n/a	n/a	n/a	n/a	n/a	n/a
	Moderate	0.758(0.0168) CI: 0.725 - 0.791)	n/a	n/a	n/a	n/a	n/a	n/a	n/a
	Severe	0.841(0.034) CI: 0.773 - 0.908)	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Binary	Moderate to severe	0.812 (0.0170) CI: (0.778 - 0.845)	79%	72%	46%	92%	2.82	0.29	73%
Binary	Mild to severe	0.800 (0.0144) CI: (0.772 - 0.828	70%	79%	74%	75%	3.33	0.38	75%

[a] See figure 2 for full description of each approach to operationalizing mobility limitation.

TABLE VI: COMPARISON OF PREDICTED TO ACTUAL SEVERITY OF MOBILITY LIMITATION FOR THE FOUR LEVEL APPROACH TO OPERATIONALIZING MOBILITY LIMITATION USING HEALTHCARE ADMINISTRATIVE DATA AMONG VETERANS IN THE WAVES STUDY WHO COMPLETED THE MEDICARE CURRENT BENEFICIARY SURVEY BETWEEN 2010-2013[a,b]

Limitation	**predicted none**	**predicted mild**	**predicted moderate**	**predicted severe**	**total**
None	368	93	26	29	516
% correct	**75%**	44%	23%	19%	
mild	86	72	29	36	223
% correct	17%	**34%**	26%	24%	
moderate	32	40	54	54	180
% correct	7%	19%	**49%**	36%	
severe	6	6	2	30	44
% correct	1%	3%	2%	**20%**	
Total	492	211	111	149	963

[a]Mobility limitation severity levels were derived the Medicare Current Beneficiary Survey on walking difficulty.

[b] See figure 2 for full description of each approach to operationalizing mobility limitation.

TABLE VII: COMPARISON OF PREDICTED TO ACTUAL SEVERITY OF MOBILITY LIMITATION FOR THE THREE LEVEL APPROACH TO OPERATIONALIZING MOBILITY LIMITATION USING HEALTHCARE ADMINISTRATIVE DATA AMONG VETERANS IN THE WAVES STUDY WHO COMPLETED THE MEDICARE CURRENT BENEFICIARY SURVEY BETWEEN 2010-2013 [a,b]

Limitation	**predicted none/mild**	**predicted moderate**	**predicted severe**	**total**
none / mild	485	128	5	618
% correct	**80%**	44%	7%	
moderate	112	149	41	302
% correct	19%	**51%**	59%	
severe	8	13	23	44
% correct	1%	4%	**33%**	
total	605	290	69	964

[a] Mobility limitation severity levels were derived from questions on the Medicare Current Beneficiary Survey on walking difficulty.

[b] See figure 2 for full description of each approach to operationalizing mobility limitation.

veterans were correctly classified as having none or mild mobility limitation, 51% were correctly classified as having moderate limitation, and 33% correctly classified as having a severe limitation.

2. **Sensitivity analysis results**

I estimated several different iterations of the 4-level measure based on different combinations of the questions but had similar results. These iterations included 1) using only the any walking difficulty and the difficulty walking ¼ mile questions, using only the needing help from another person and the any difficulty walking questions, and using only the needing help from another person and the difficulty walking ¼ mile questions. None of these produced any better results then what is shown in Table VI,

In Table IX, I show that the model using a one-year window was tested for the binary mild to severe variable and it had similar results to the two-year window, but slightly worse, as it had a lower AUC (0.753) and lower sensitivity (70%) and specificity (71%). In the more generalizable model, where I removed VA specific measures, the model had similar performance properties to the original model. This was partly because new measures took the place of the ones removed. In this model, age became a significant predictor. This reflects a high collinearity with age and copayment group, so that when copayment group was removed, age was kept as a significant predictor. The difference here is that age is a negative coefficient, indicating that younger adults in this sample were more likely to be disabled. This finding makes sense because those under 65 in Medicare are only eligible due to disability status. The full regression models for the 1 year time window and the generalizable model are in and Table XXV, Appendix A. Finally, including a variable for the length of time from the interview to diagnosis was not a significant predictor and so was left out.

3. **Preferred model**

The preferred model for operationalizing mobility limitation that will be used in chapters two and three is the binary mild-to-severe mobility limitation model. The multi-level models did not perform well enough across all levels of mobility limitation. Taking into account all the model performance metrics, mild-to-severe binary model had higher performance than the moderate-to-severe binary model. Importantly for

TABLE VIII: SENSITIVITY ANALYSIS OF A MODEL TO PREDICT MILD TO SEVERE MOBILITY LIMITATION AMONG VETERANS IN THE WAVES STUDY USING DIFFERENT TIME WINDOWS AROUND THE INTERVIEW DATE FOR THE MEDICARE CURRENT BENEFICIARY SURVEY (MCBS) AND ONLY GENERALIZABLE PREDICTORS

Binary mild to severe approach	**AUC (SE) and CI**	**Sensitivity**	**Specificity**	**PPV**	**NPV**	**LR+**	**LR-**	**%correct overall**
Original 2-year window[a]	0.800 (0.0144) CI: (0.772 - 0.828	70%	79%	74%	75%	3.33	0.38	75%
1-year window[b]	0.753 (0.0158) CI: (0.722 - 0.784)	70%	71%	73%	67%	2.41	0.42	70%
Generalizable outside VA[c]	0.7944 (0.0145) CI: (0.766 - 0.823)	70%	76%	71%	74%	2.92	0.39	73%

[a]Original two-year window was two years before the MCBS interview date and six months after.

[b] One-year window was one year before the MCBS interview date and three months after.

[c] In the model generalizable outside the VA, VHA copayment group, marital status, and BMI were removed as potential predictors.

use in chapters two and three, the mild-to-severe version had a high PPV. Lastly, the mild-to-severe model only needed to use two of the MCBS questions and both were asked to all 964 subjects.Whereas, to arrive at the moderate-to-severe model, the questions on use of assistive devices for walking and need for help from another person were used but these were only answered by those who answered yes to having ‘any difficulty walking’ question. Thus, the moderate-to-severe version is partially based on a smaller sample.

E. Discussion

The objective of this study was to develop a novel algorithm using healthcare administrative data to predict mobility limitation in a sample of veterans who answered questions on mobility limitation on the Medicare Current Beneficiary Survey. I aimed to show that in the absence of self-reported mobility limitation, healthcare administrative data alone could be used to reliably identify people with mobility limitation. I developed several alternate algorithms based on different forms of a mobility limitation outcome and tested their performance. I show that the algorithms for predicting a binary mobility limitation outcome performed well at discriminating between people who did and did not have mobility limitation. However, for the multi-level mobility limitation outcome, the predicted levels of mobility limitation severity did not match well with the actual severity levels.

My study contributes to the current literature on health services and health outcomes among people with mobility limitation by developing a tool that can be used to identify people with mobility limitations in healthcare administrative data. Identifying people with mobility limitation in healthcare administrative data is an important supplement to existing research approaches for monitoring health outcomes over time and in relation to interventions or policy changes within healthcare systems. Because my approach in this study uses self-reported mobility limitation as the gold standard criterion, those identified by the algorithm are a different group of people than might be identified by simply selecting those with wheelchairs or those with particular conditions known to be associated with mobility limitations (e.g. Spinal Cord Injury, Multiple Sclerosis, Stroke). Because not everyone with a specific condition has a mobility limitation and not everyone who has a mobility limitation receives a wheelchair (Iezzoni, 2002), the mobility limitation algorithm developed in this chapter provides a more accurate definition of mobility limitation that can be used in studies with access to healthcare administrative data. Finally, my approach allows for reporting on the level of sensitivity and specificity of the algorithm, which is not possible without systematically comparing healthcare administrative data with a gold standard criterion for mobility limitation.

1. **Comparison of multi-level and binary approaches**

Similar to Davidoff et al. (2013), I had difficulty discriminating between mobility limitation severity levels. In their study, they could not develop a model that was sufficient to distinguish a middle ‘some disability’ category. In a study about the consistency of the disability questions on the American Community Survey, Ward et al. (2017) highlighted the temporal nature of mobility limitation. They showed that only 39% of respondents with mobility limitation consistently reported having one within the same year. The middle or “some” category may be people with temporal or milder mobility limitations that can vary over time. A challenge of using healthcare administrative data is that the data do not necessarily indicate the severity of a diagnosis or procedure. For instance, we are not able to distinguish between mild osteoarthritis and severe osteoarthritis or where someone might be in the progression of Multiple Sclerosis that leads to greater mobility limitation. Identifying new predictors in healthcare administrative data that reliably indicate the severity of conditions could help distinguish between mild, moderate, and severe limitations in the future. For now, a binary mobility limitation algorithm is a useful foundation to begin to study mobility limitation using healthcare administrative data.

The AUC for several of the outcomes was near or above 0.8, which means the model is considered good at discriminating between those with and without mobility limitations. These AUC value are within a similar range of algorithms on having any ADL limitation by Ben-Shalom (AUC = 0.75), Faurot (AUC= 0.85). The specialized equipment variable had a lower AUC at 0.75. This may be because only people who answered yes to the first having any walking difficulty item were asked the question on using special equipment. Thus, the model compared those with walking difficulty who use specialized equipment to those with walking difficulty who do not use specialized equipment. There may be several predictors that those with difficulty walking who do and do not use specialized equipment have in common, making discriminating between the two more challenging. It was not feasible to assume that those who answered 'no' to the initial 'any difficulty walking' question do not use specialized equipment. In fact, there were 58 (17%) respondents who answered no to the initial walking question but had a record of receiving an assistive mobility device.

2. **Role of environmental factors**

Assistive mobility devices are critical variables for identifying mobility limitation as they were the strongest predictors in every model. Davidoff et al. (2013) and (Faurot et al., 2015) also found that having a wheelchair or hospital bed were strong predictors in their models. My approach was somewhat different in that I combined hospital beds with other types of home modifications, such as lifts or ramps. The strong predictive value of assistive mobility devices may reflect the fact that they are used by people across health conditions who have a mobility limitation.

Among those with each type of assistive mobility device, there were between 1.1% and 5% who responded that they do not have difficulty walking. This finding shows how relying simply on assistive devices is not a reliable approach to identifying a sample with mobility limitations. It may also reflect how assistive mobility devices help people walk who may otherwise report greater difficulty. Since the results are self-reported, they may feel they do not have a limitation when they walk with a cane. Alternatively, these could be people who received a device as part of rehabilitation and then no longer use it.

Neighborhood socio-economic status (SES) may play an important role in contributing to mobility limitation among veterans. The percentage of people below the federal poverty line and median household income were significant predictors in some of the models I tested. The contributing role of neighborhood SES aligns with how the ICF identifies environmental factors as interacting with personal factors and health conditions to affect mobility limitation. In my study, people living in a census tract with a higher percentage of individuals below poverty were more likely to report mobility limitation. Similarly, being in a census tract with a higher median income was associated with a higher likelihood of reporting a mobility limitation. These findings affirm the dynamic relationship between poverty and disability that are well documented in the literature (Iezzoni, McCarthy, Davis, & Siebens, 2001; Lauer & Houtenville, 2018; Palmer, 2011). Being in poverty can lead to disability and disability can lead to poverty as a result of a lack of employment.

Census division, and in particular the West South Central division was a consistent predictor of mobility limitation. There may be certain aspects of the policies and treatments (or lack thereof) for mobility limitation that that differ by census divisions. Different State policies, or different healthcare practices that have been shown to vary by Veterans Integrated Services Networks (VISN) (Hubbard Winkler et al., 2010) may account for some of this regional variation.

3. **Importance of health conditions**

Across my models, having a disease of the central nervous system, or of the musculoskeletal system and connective tissue were consistent predictors. Faurot et al. (2015) found heart disease, stroke, paralysis, the difficulty walking diagnosis and diabetes to be some of the strongest predictors. Each of these were predictors in some of my models but not all. This may reflect differences in our outcomes. Faurot and colleagues were seeking to predict 'any limitation' and I was focused on mobility limitation. Davidoff et al. (2013) also looked at 'any limitation' and found that a nursing home visit or hospice visit were the strong predictors. Nursing home and hospice visits were not included in my study as potential predictors and may be an important consideration in the generalizability of my results to other studies that want to include those with a nursing home visit.

4. **Use of the mobility limitation algorithm in future research and evaluation**

The coefficients reported in Table IV can be used by other researchers to predict mobility limitation using healthcare administrative data. In Table XXV, Appendix A, I also provide the cut-offs that are recommended to achieve a balance of high sensitivity and specificity for the binary models. The decision of the cut-off is based on the researcher's particular aim (Streiner & Cairney, 2007). There may be reasons for changing the cut-off to have a model that is more sensitive or more specific (Chubak, Pocobelli, & Weiss, 2012). For instance, a researcher may want to use a more sensitive cut-off as a screening tool, to first capture all potential individuals with a mobility limitation, and then apply a more specific tool to weed out false positives. A more sensitive cut-off would be created by simply lowering the cut-off so that more people are included as having mobility limitation.

There are many pressing public health strategies that could benefit from using healthcare administrative data to evaluate outcomes for people with mobility limitations. For instance, previous research has highlighted the absence of accessible weight scales as an environmental barrier to weight loss among people with mobility disabilities (Iezzoni, 2011; Locatelli & LaVela, 2016). Evaluating whether a policy requiring accessible weight scales in all primary care facilities reduces obesity among individuals with mobility limitations would require a mobility limitation definition that cuts across assistive devices and specific health conditions. As suggested by D. Carroll, Cochran, Guse, and Wang (2012), it is important to understand whether training physicians to recommend physical activity for patients with mobility limitations helps reduce the high rates of physical inactivity and subsequent health outcomes in this population. Such questions require identification of people with mobility limitation as a subgroup and require data that are not currently available in national surveys or clinical research. Survey data are usually cross-sectional and insufficient for following a cohort of people with mobility limitations over time and in relation to a specific policy change or intervention (Livermore, 2007).

There are currently various public health strategies that aim to address health disparities for people with mobility limitations. These are related to transportation, home modifications, and pedestrian infrastructure. There have been initiatives to make it easier for veterans and Medicaid recipients with mobility limitations to schedule and use local transit, or door-to-door services (National Academies of Sciences, 2016). Through the CDC NCBDDD, there is a focus on making health promotion programming accessible to people with mobility limitations (National Center on Birth Defects and Developmental Disabilities, 2019). For instance, the Diabetes Prevention Program (DPP), is being used across the U.S. and recent funding has gone into reaching populations with mobility limitations (Betts, Froehlich-Grobe, Driver, Carlton, & Kramer, 2018). The US Surgeon General’s call to action on walking and walkability describes the need for policy, systems, and environmental changes that promote walking among people with mobility limitations. (US Department of Health and Human Services, 2015) In order to further public health initiatives to improve health for the broad group of people with mobility limitations, it is highly critical that researchers be able to identify and study the health of this group using new data sources, such as healthcare administrative data. Once mobility limitation is identified in healthcare administrative data, it can also be linked to other data, such as participation in the VA’s MOVE program, or the VA’s door-to-door services to understand how well these programs are working for this specific population.

As a next step, testing the algorithm in a different sample is necessary to validate the algorithm. To do so, data are needed for a similar gold standard criterion that is used in this chapter. A similar approach as was used in this chapter could be tested to expand the mobility limitation algorithm to people with acquired and congenital mobility limitations. Another direction for research on mobility limitation using healthcare administrative data is to identify when mobility limitation decreases in severity or is no longer a problem. This would help in distinguishing between those with temporal mobility limitations from those with permanent mobility limitations.

F. <u>Limitations</u>

A limitation of the NPPD data is that although there is a record that a veteran received an assistive mobility device, it is challenging to identify whether they actually used it or for how long. Additionally, it is possible that hospital beds are provided for reasons unrelated to mobility. Some veterans may have received an assistive device for a temporary limitation and if their mobility improved, they may then report no difficulty walking. However, I did not include devices that are specifically designed for temporary conditions such as crutches. There are variables that may predict mobility limitation that were currently unavailable, such as individual income, education, years of military service, etc. There could be mistakes in coding of diagnosis (Peabody, Luck, Jain, Bertenthal, & Glassman, 2004), but I attempted to deal with these by requiring two codes greater than 30 days apart for outpatient visits. I attempted to use all the codes available in the literature related to mobility limitation, but there may be some that were not included. Because of the smaller sample, I had to combine similar codes. With a larger sample, it may be possible to use more individual ICD9 diagnosis codes to tease out any heterogeneity within ICD9 code groups. However, I was able to show that using ICD9 code groups had good predictive properties. The MCBS sample is focused on those over 65 as well as those under 65 who may have a disability. I cannot generalize to populations outside the VA, such as individuals with congenital disabilities. The sample overall was smaller than other studies that have worked on disability algorithms (Ben-Shalom & Stapleton, 2016; Faurot et al., 2015). However, those studies were attempting to predict any type of limitation in activities of daily living (ADLs). Because I was predicting a specific limitation (mobility) the smaller sample size is expected. Additional testing is needed to validate the algorithm and refine it so that it is generalizable beyond the VA.

G. <u>Conclusion</u>

In this study, I showed that in the absence of self-reported mobility limitation data, it is possible to identify people with mobility limitations using a predictive algorithm composed only of healthcare administrative data. Healthcare administrative data provide a new opportunity for studying public health priorities for people with mobility limitations. The algorithm developed in this chapter can be useful for defining cohorts of people who have a mobility limitation and studying their health over time. The algorithm can be a supplemental tool for evaluation and monitoring that is part of existing State and National surveys. In order to address health disparities that have been documented for people with mobility limitations, the mobility limitation algorithm can be used to evaluate environmental, policy, or systems changes that are implemented in Veterans Health Administration, and with some additional refinement, in other health care settings as well.

II. DOES A MOBILITY LIMITATION LEAD TO INCREASED BMI? A LONGITUDINAL STUDY TO TEASE OUT EFFECTS OF MOBILITY LIMITATION ON BMI USING A LARGE NATIONAL DATASET OF VETERANS

A. Introduction

An estimated 31.5 million US adults have a mobility limitation, comprising the largest category of people living with a single functional limitation type (Courtney-Long et al., 2015). A large body of research has documented a higher prevalence of obesity among people with mobility limitations (An et al., 2015; Froehlich-Grobe, Lee, & Washburn, 2013; Rasch, Hochberg, Magder, Magaziner, & Altman, 2008; Reichard et al., 2011; Weil et al., 2002). However, much of what we know about mobility limitation and obesity comes from cross-sectional studies. It is important to understand whether people with mobility limitation are at a higher risk for increases in BMI. Understanding such risks can help in developing more targeted efforts for obesity prevention as well as a better understanding of the mechanisms by which people become obese. If mobility limitation leads to higher BMI, it is also important to understand the magnitude of that effect and to be able to develop realistic interventions that appropriately address such a magnitude. If the effect size is large, interventions might focus on prevention of weight gain as a primary goal. If mobility limitation does not lead to an increase in BMI (e.g. decrease or no effect), the strength of the association between mobility limitation and obesity identified in cross-sectional studies may be driven by unobserved factors that are not measured in cross-sectional studies. Certain personal factors, such as age or current BMI, may also differentially lead people with mobility limitations to gain more weight and these are also important to identify and study.

Despite the disproportionately higher rate of obesity among people with mobility limitations, the current literature on mobility limitation leading to obesity is minimal and has not addressed unobserved heterogeneity that may bias results. There are methodological challenges to identifying a study design that supports causal interpretation of the effect of mobility limitation on obesity, namely the fact that obesity can also cause mobility limitation (Vincent et al., 2010). In cross-sectional studies, the estimated effect includes the effect of mobility limitation on BMI and the effect of obesity on mobility limitation.

Previous research has suggested that the effect of mobility limitation on BMI varies by age, level of comorbidities, and baseline weight. de Munter et al. (2016) conducted a study of a population-based cohort in Sweden; the study's findings suggest that mobility limitation was associated with a small increase in BMI in younger and middle aged adults over an 8-year period, but showed no association for older adults. Developing a mobility limitation in older adults, however, has been shown to be associated with both weight gain and weight loss (Forman-Hoffman et al., 2008; St-Arnaud-McKenzie, Payette, & Gray-Donald, 2010). Comorbidities were discussed as potential reasons for the bi-directional associations, but this has not been tested. Finally, previous research suggests that those who were obese had different trajectories of BMI change after mobility limitation compared to people who were underweight or of normal weight (Powell, Affuso, & Chen, 2017). A challenge that previous studies experience is smaller sample sizes that may make stratified analyses not feasible (Livermore, 2007).

This chapter contributes to the existing literature by examining the risk of an increase in BMI for people with a mobility limitation using a robust study design and 'big data' on 3.2 million veterans who were included in the Weight and Veterans Environments Study (WAVES, NIH R01 (R01CA172726, VA IIR 13-085)) (Zenk et al., 2018). I address important concerns of unobserved heterogeneity through the use of fixed-effects models to control for time-invariant unobserved variables and concerns of reverse causality of obesity causing mobility limitation through the use of a one-year lag for mobility limitation. Under the assumption that there are no time-varying omitted variables, the estimated effect of the lagged mobility limitation variable can be interpreted as a causal effect on BMI.

In this chapter, I utilize a novel approach to identify individuals with mobility limitation in healthcare administrative data that facilitate 'big data' research without needing additional efforts to survey veterans or conduct extensive physical tests on limitations in mobility functioning. 'Big data' research on people with mobility limitations is only possible with an extensive set of potential predictors that can account for health conditions, assistive devices, personal characteristics and environmental factors—all of which contribute to and reflect aspects of a mobility limitation, yet are not sufficient to identify mobility limitation on their own (Iezzoni, 2002). Being able to accurately classify a large sample as having a mobility limitation and not having a mobility limitation is necessary for estimating the effect of mobility limitation while accounting for the average change in BMI that an individual would have experienced had they not had a mobility limitation.

The large sample, derived from healthcare administrative data, supports exploration of the effect of mobility limitation on BMI across age groups, BMI category, and comorbidity. In other words, we can identify what unique combinations of people with mobility limitations and other factors are at higher risk for changes in BMI following an acquired mobility limitation. These results can inform the development of more targeted interventions and establish clearer expectations about change in BMI over time.

B. Background

1. Current knowledge about obesity among people with mobility limitations

Preventing secondary health conditions among people with mobility limitations has been a public health goal in the U.S. for several decades (Pope & Tarlov, 1991; U.S. Department of Health and Human Services, 2005). A secondary health condition is a preventable condition that results from a primary disabling condition (Pope & Tarlov, 1991). For example, a pressure ulcer is a secondary health condition for people with lower-limb paralysis that results from lack of bodily movement when someone is in a wheelchair or bed for many continuous hours. Pressure ulcers can be prevented through regular movement, or periodically shifting or turning the body (Bluestein & Javaheri, 2008).

Similarly, obesity has been described as a secondary health condition for people with mobility limitations (Pope & Tarlov, 1991; Rimmer, 1999), and studies have examined obesity as a secondary health condition among people with mobility limitations (Nosek et al., 2006). The rationale is that because people with mobility limitations are more sedentary, they are more likely to gain weight (Liou, Pi-Sunyer, & Laferrere, 2005). The high rate of physical inactivity was shown in a study on health behaviors using data from the National Health Interview Survey (NHIS) from 2009-2012, which reported that the rate of physical inactivity among people with mobility limitation was 57.4% compared to 26.1% for those without mobility limitations (C. Carroll et al., 2014). Research has documented the higher rates of obesity among people with disabilities (Froehlich-Grobe et al., 2013), and when broken up by type, for those with mobility limitations (Nosek et al., 2006; Rasch et al., 2008; Reichard et al., 2011; Weil et al., 2002).

Reducing obesity among people with disabilities, including those with mobility limitations, has been defined as a health equity priority (Fox et al., 2013; Krahn et al., 2015). In other words, because the disparity in obesity between those with and without mobility limitations is so high, it is an important public health goal to address. Obesity is a major concern because it leads to greater levels of chronic diseases (Kopelman, 2007; Must et al., 1999), increased risk of disability (Peeters, Bonneux, Nusselder, De Laet, & Barendregt, 2004), and mortality (Flegal, Graubard, Williamson, & Gail, 2007; Hruby et al., 2016). Obesity is considered a preventable condition that can be managed through behavioral changes in physical activity and nutrition habits (Centers for Disease Control and Prevention, 2018b).

Despite the focus on obesity as a significant public health issue, few studies have examined obesity as a secondary health condition resulting from having a mobility limitation. In other words, limited research has examined whether developing a mobility limitation causes an increase in BMI. The existing research is mostly cross-sectional; several cross-sectional studies have shown strong associations between mobility limitation and obesity. Kinne, Patrick, and Doyle (2004) reported that disability (including mobility) was the largest predictor in adjusted models predicting excess weight problems using data from the Behavioral Risk Factor Surveillance System (BRFSS). Nosek et al. (2006) found that among women with physical disabilities, obesity was reported among 48% compared to 34% of women in the general population. Weil et al. (2002) used data from the NHIS, and found that the highest risk for obesity among people with any disability was among people with mobility limitations (some limitation - AOR: 2.4, 95% CI: 2.3-2.5, severe limitation – AOR: 2.5, 95% CI: 2.3-2.7). Further, An et al. (2015) studied obesity among people with mobility limitations using pooled-years of data from the National Health and Nutrition Examination Survey (NHANES). They found that having a mobility limitation was associated with increased odds of obesity (OR = 1.54) and extreme obesity (OR = 1.85). While these analyses controlled for several potential confounders, they cannot be interpreted as indicating that mobility limitation leads to higher BMI.

2. **Limitations of cross-sectional studies**

The estimates from these cross-sectional studies are biased because they do not address unobserved heterogeneity. In other words, the estimates are biased because there may be unobserved factors that are associated with both BMI and mobility limitation. A key assumption of ordinary least square regressions is that there are no omitted variables that are correlated with the predictor and the outcome (Wooldridge, 2015). So cross-sectional studies that do not account for omitted variable bias violate this assumption and potentially inflate the strength of the association between mobility limitation and BMI. Without a strategy to address causality, such studies do not account for the average trajectory of weight gain that might be observed among people without a mobility limitation. In other words, findings from cross-sectional studies do not identify whether an increase in BMI is because of the mobility limitation, or whether mobility limited individuals would have had a similar increase in BMI even without the mobility limitation. This is significant to understand in order to establish that a mobility limitation actually leads to increases in BMI.

Finally, and perhaps most importantly, cross-sectional studies are problematic because the cross-section includes both individuals who developed mobility limitations as a result of obesity and individuals with an existing mobility limitation who became obese (de Munter et al., 2016). The strong associations observed between mobility limitation and obesity in previous research reflects both of these effects. This bi-directionality or reverse causality limits our ability to draw conclusions about whether mobility limitation affects obesity or vice versa. Teasing out the causal effects can enable us to better understand which types of prevention efforts will have the most impact on reducing the large disparities in obesity between people with mobility limitations and those without.

3. **Evidence from longitudinal studies**

An extensive body of research has examined how obesity affects mobility limitation (Vincent et al., 2010). Obesity can affect mobility limitation through osteoarthritis (Guh et al., 2009; Tukker, Visscher, & Picavet, 2009), and in some cases, lower-limb amputations resulting from diabetes complications among obese individuals (Centers for Disease Control and Prevention, 2011; Littman et al., 2015). In addition, obesity is associated with a greater likelihood of falls and injuries that lead to mobility limitations (Xiang, Kidwell, & Wheeler, 2008). The literature on the effect of mobility limitation on obesity is far less extensive, however.

There are two sets of studies that provide some evidence regarding the effect of mobility limitation on BMI. The first set focuses on studies of people with specific health conditions that are associated with mobility limitation, and specifically are about those with spinal cord injury (SCI), and amputation. These studies are strengthened by more detailed and objectively measured data on both mobility limitation and BMI that are a part of healthcare administrative data, but have small sample sizes and cannot be generalized to a broader group of people with mobility limitations. The second set is comprised of population-based studies, such as those originating from nationally representative surveys that examine people with self-reported mobility limitation. These analyses benefit from large sample sizes, but utilize more subjective and less reliable measures of mobility limitation (Livermore, 2007) as well as of BMI that come from self-reports. Findings from both sets of studies indicate that mobility limitation is associated with an increase in BMI, but that there are important factors to consider as effect modifiers.

4. **Longitudinal findings on specific health conditions**

Studies of specific health conditions associated with mobility limitation indicated varying trajectories of change in BMI. One study on veterans with lower-limb amputations indicated a substantial increase in weight of 6 to 18 pounds compared to a matched sample with no lower-limb amputation over a 2-year period, but was followed by weight loss in the third year (Littman et al., 2015). Weight gain was attributed to more sedentary time and depression, and weight loss was attributed to reductions in depression as well as onset of new comorbidities (Littman et al., 2015). People with spinal cord injury have mobility restrictions as a result of their injury that range from mild to complete (de Groot et al., 2014). Studies that tracked weight after a spinal cord injury showed varying trajectories in BMI. de Groot et al. (2014) studied a sample of 204 people with SCI and identified that more than half of the sample had stable BMI in the five years after their injury. However, the other half had increases in BMI either early on or later during the study period. The magnitude of the increase was approximately 4.0 BMI units. A larger study completed by Powell et al. (2017) investigated change in BMI among 1,094 individuals with spinal cord injury and found an overall decrease in BMI in the year after their injury. They found that the decrease was associated with level of BMI prior to injury. Being underweight or of normal weight prior to injury led to weight gain, and being overweight and obese led to weight loss (Powell et al., 2017). The main limitation of these studies on people with amputations and spinal cord injuries is that they are not generalizable to the broader group of people with mobility limitations. Additionally, Powell et al. (2017) and de Groot et al. (2014) did not have comparison groups without mobility limitations to account for average trajectories of change in BMI. Nonetheless, these studies suggest that BMI category prior to having a mobility limitation is an important potential moderator of the relationship between mobility limitation and BMI that requires further investigation.

5. **Findings from population-based survey research**

The second set of studies that used national survey data suggest that the effect of mobility limitation on BMI varies by age and comorbidity. Forman-Hoffman et al. (2008) studied older adults in the Medicare Current Beneficiary Survey and factors associated with 5% weight gain and loss. Their approach was strengthened by using a generalized estimating equation (GEE) that accounted for repeated measures and a lag for increased mobility limitation to address reverse causality. They found that older adults ages 53-71 with increased mobility limitation had increased odds of >5% weight gain (OR =1.58 in men and OR = 1.55 in women) but also increased odds of >5% weight loss (OR =1.72 in men and OR = 1.54 in women). St-Arnaud-McKenzie et al. (2010) similarly found that mobility limitation was associated with weight gain and weight loss among older adults ages 67-86. Weight loss was discussed as being related to poorer health status that affected sufficient energy consumption and which was sometimes coupled with hospital stays or extended rehabilitation (Forman-Hoffman et al., 2008; St-Arnaud-McKenzie et al., 2010). Although the comorbidities and other functional limitations were controlled for, there was no examination of how the effect of mobility limitation on BMI varied across different levels of comorbidity. These studies were also limited by their focus on older adults. Studying mobility limitation across the lifespan is especially important for veterans, who can experience mobility limitations earlier in life due to their role in the military. Additional analysis that examines a sample across age groups is needed to further understand how the effect of mobility limitation varies by age.

Thus far, only one study has examined a sample across age groups to understand how the effect of mobility limitation varies by age. In a population-based study in Sweden that examined respondents over two periods of time (8-years apart), younger (ages 18-39) and middle aged (ages 40-55) adults, who either gained a new mobility limitation or had an existing one, had higher increases in BMI from a mobility limitation compared to older adults (ages 56-84), who did not gain any more weight compared to older adults without mobility limitations (de Munter et al., 2016). The magnitude of the effect of mobility limitation on BMI ranged from 0.49 (95% CI, 0.20 – 0.77) in middle age adult males to 1.41 (95% CI, 0.94-1.87) in younger adult females. However, this study used a crude self-reported measure of mobility limitation that is not common in US surveys. Their survey asked if the respondent was ‘confined to a bed’ or ‘have some problems in walking about’. Additionally, BMI was self-reported and so is less reliable than an objective measurement (Nawaz, Chan, Abdulrahman, Larson, & Katz, 2001). Finally, their methods do not discuss any steps to address unobserved heterogeneity.

In sum, findings from the current literature suggest that the differential effects of mobility limitation on BMI may be attributed to key modifiers, namely age, comorbidity, and baseline weight status. In order to understand the role of these potential modifiers in helping to explain the change in BMI observed after a mobility limitation, additional research is needed—research using a large enough sample that allows for stratified analysis.

6. Contribution

Because a limited number of studies have examined the effect of mobility limitation on BMI, it is unclear whether people with mobility limitations are at a higher risk for increases in BMI. The existing literature that describes a strong association between mobility limitation and obesity does not provide the necessary evidence to establish a higher risk. To address this gap, I leverage a large, longitudinal dataset developed for the Weight and Veterans Environments Study (WAVES NIH R01 (R01CA172726, VA IIR 13-085)), which used ‘big data’ from the Veterans Health Administration (VHA) (Zenk et al., 2018). This chapter contributes to the literature by estimating the effect of mobility limitation on BMI using a study design that addresses the unobserved/unmeasured heterogeneity in factors that are fixed over time and which have limited causal interpretation in previous research.

Healthcare administrative data from the VHA provide a unique opportunity for studying a large population of the same individuals over time. The WAVES dataset contains information on demographics, diagnoses, health care utilization, and durable medical equipment. I utilize a novel approach to identify a large group of individuals with mobility limitation in healthcare administrative data. Because mobility limitation cannot be defined simply based only on assistive mobility devices or specific health conditions (Iezzoni, 2002), the approach used in this chapter is based on a predictive algorithm with good sensitivity and specificity. The algorithm allows for identifying a large, broad population of veterans with mobility limitations as well as delineating those without a mobility limitation.

The strategy used in this study takes advantage of the repeated measures on the same individuals to examine within-person change over time. Because of the focus on within-person change, factors that do not change over time within the individual are removed as potential confounders of the relationship between mobility limitation and BMI. This is accomplished through inclusion of individual fixed effects within the model estimation. Under the assumption that there are no time-varying unobserved variables that are correlated with mobility limitation and BMI, the results can be interpreted as causal. Because WAVES includes multiple years of data, I am able to use a lagged mobility limitation variable to address concerns of reverse causality that obesity causing the mobility limitation is reflected in the estimate of mobility limitation on BMI. In other words, the lag helps establish the direction of a cause (mobility limitation) coming prior to the effect (BMI). Estimates obtained from the lagged mobility limitation variable reflect the effect of mobility limitation in the past year on BMI in the present year. Another strength of WAVES is that it includes objectively measured weight and height data, which have not been available in many of the previous studies that used self-reported weight and height collected in national health survey data.

Finally, using the WAVES dataset provides the opportunity to conduct stratified analysis to identify subgroups at highest risk of weight gain after a mobility limitation. Previous research has indicated that the variation in the effect of mobility limitation on BMI may be related to age, comorbidity, and baseline weight status. The large dataset used in this study supports a stratified analysis without concern for a loss of statistical power. Results from such stratified analysis can inform prevention efforts by suggesting which subgroups of people with mobility limitation should be considered the highest priority and that prevention efforts will have the largest potential impact on. For some, a mobility limitation may lead to an increase in BMI, whereas for others, it may lead to a decrease or simply have no effect.

7. **Purpose**

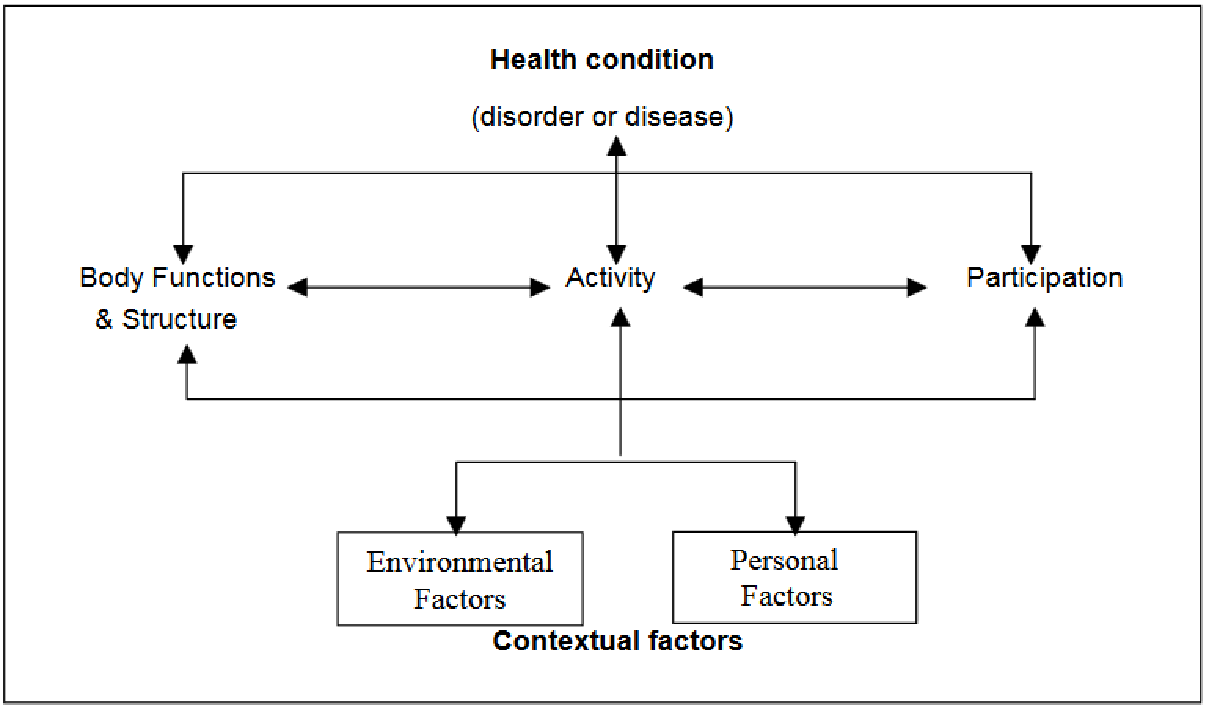
The purpose of this study is to examine if and to what extent BMI increases after an acquired mobility limitation, and to identify which subgroups among those with a limitation may be at higher risk of increased BMI. The research questions are:

1) What is the effect of a mobility limitation on BMI among a national sample of veterans?
2) How does the effect of a mobility limitation on BMI vary by age, comorbidities, or baseline weight status? Are there certain groups with higher risk of increased BMI from a mobility limitation?

8. **Conceptual model**

The International Classification of Function, Disability and Health (ICF) is a biopsychosocial model of health and function that serves as a conceptual framework and an important tool for studying disability (see Figure 3). The ICF was developed by the World Health Organization (WHO) as a classification of disability and health. The ICF incorporated a social model, which views disability as also created by societal and environmental factors (World Health Organization, 2001). In the ICF, human functioning is expressed across three domains of body function/structure, activities, and participation. Individuals can experience limitations in any one of these domains or across multiple domains. Functioning is moderated by environmental, personal factors, and health conditions (World Health Organization, 2001). The arrows in the ICF model are bi-directional to show how the domains, health conditions, and contextual factors can influence each other.

Figure 3: International Classification of Function, Disability and Health (ICF) (World Health Organization, 2001)



Similar to ICD9 and ICD10 codes, the ICF is also a classification system. Instead of codes for specific diagnosis and procedures, the ICF classifies functioning and disability into specific codes across the domains and factors (World Health Organization, 2001). Mobility is a subdomain within the activity domain. Mobility limitations include difficulty with several physical tasks, including walking, climbing stairs and transferring in various environments (Patla & Shumway-Cook, 1999). The phrase 'disability' is not one of the factors in the ICF and so is not the same as a mobility limitation. In the ICF, mobility disability is seen as an interaction between the three domains, health conditions, and contextual factors. The ICF has been used to examine empirical relationships between its component factors and health outcomes (Robinson & Butler, 2011) or to develop more detailed conceptual models, such as the model of physical activity and disability (van der Ploeg et al., 2004). In this chapter, I use the ICF to examine how mobility limitations (a limitation in the activity domain) may affect weight change (a health condition), given a set of time-varying personal and environmental factors. In my third chapter, I incorporate additional environmental factors on walkability of neighborhood into the analysis and examine interactions between walkability and mobility limitation.

In Figure 4, I illustrate how the specific variables that I am using in this study align with the different components of the ICF. I examine interactions between comorbidity and mobility limitation, age and mobility limitations, and baseline weight status and mobility limitation. This corresponds to the ICF in terms of interactions with personal factors and an activity limitation and with health conditions and an activity limitation.

C. **Methods**

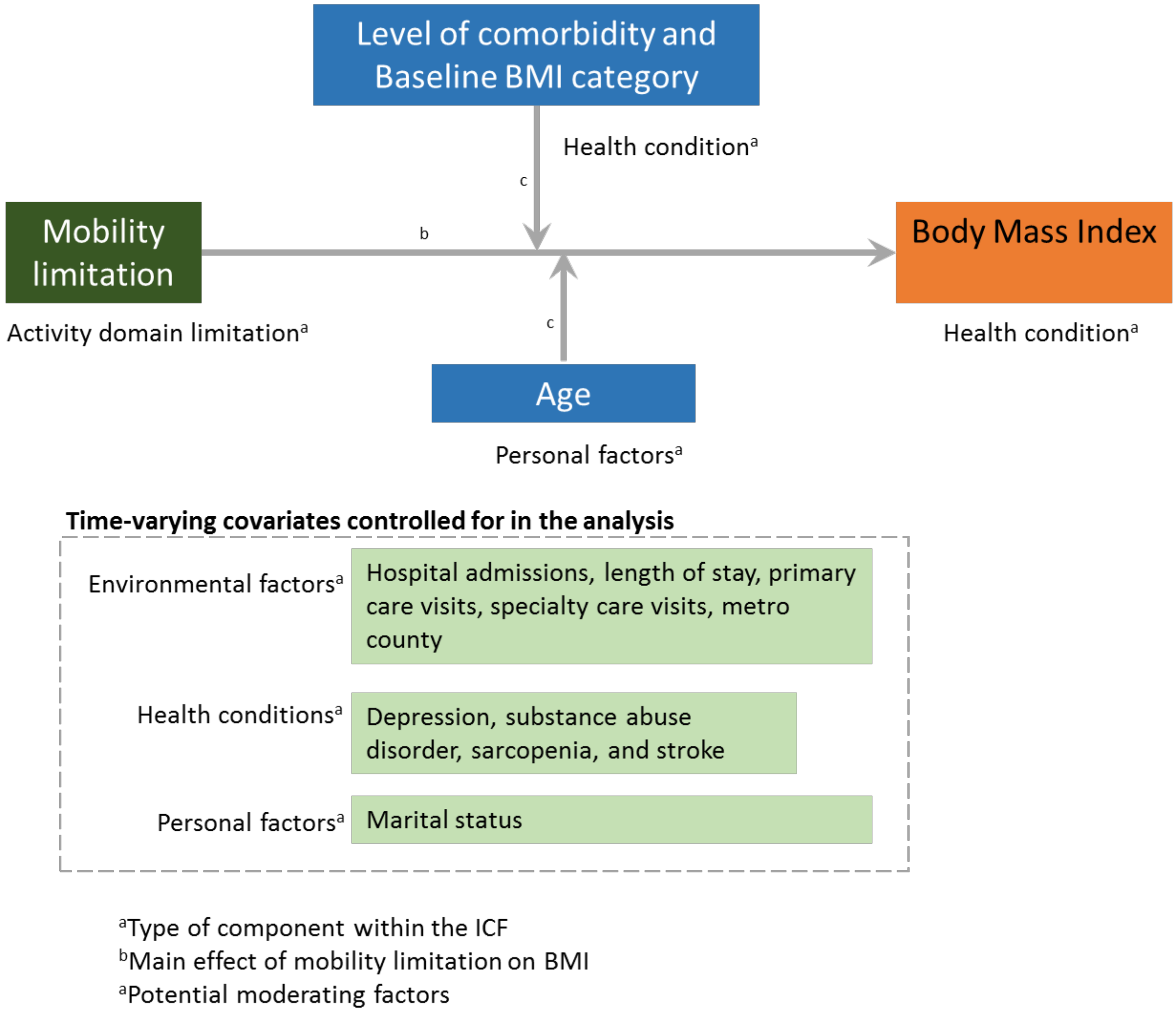
1. **Data sources**

The dataset used in this analysis is from WAVES, which developed a longitudinal cohort of veterans using data housed in the VHA Corporate Data Warehouse (CDW), such as electronic health records, durable medical equipment, and Medicare claims (Zenk et al., 2018). These data include ICD9 diagnosis codes, procedure codes, and healthcare utilization. Durable medical equipment included data on assistive mobility devices as well as other equipment used by people with mobility limitations, such as ramps or lifts in a home (Department of Veterans Affairs, 2014). The development and merging of the data as an annual panel in the long form has been described previously (Zenk et al., 2018). Data from Medicare claims were not available for the years 2014 and 2015.

2. **Sample**

Because data from WAVES come from healthcare administrative data and are not collected on set time-interval, WAVES is an unbalanced panel dataset. Veterans have between 2-6 years in the study and there can be gaps. Gaps in the panel reflect years when a veteran did not visit the VA and have their weight measured. Thus, years with missing BMI do not contribute to the data in that year.

Figure 4: Illustration of How Components from the ICF were Operationalized in this Study



The inclusion criteria for WAVES was veterans having at least one visit to a VA facility in the two years prior to their baseline year. The visit could be for inpatient or outpatient services. The sample included veterans ages 20-80 at their first visit in the study period.

The WAVES data include 3,263,306 veterans with 20,893,557 person-year observations. Veterans were excluded who (1) had no height measurement, (2) were without at least two weight measurements, (3) had no geocodable home address for any of the years, or (4) had a long nursing home stay at baseline (greater than 90 days). There were 2,307,882 person-year observations with missing BMI. I excluded the person-years of individuals who had an amputation for the year of the procedure and any year after. Amputations were defined by ICD9 procedure codes. Not excluding the years that an individual had an amputation and after could skew the data because of a potentially large decrease in weight as a result of the amputation. There were 39,184 veterans who had an amputation during the study. I excluded 170,860 person-year observations for the years during and after an amputation.

I also excluded records in years after an individual died. This may occur when some administrative records do not catch up to the death records. Death records are a set of administrative data from the VHA Vital Status Master File, which combines records from VHA hospitals, family members applying for death benefits, VA National Cemetery Administration, hospital inpatient stays, reports to the Social Security Administration, and the Medicare vital status file (Sohn, Arnold, Maynard, & Hynes, 2006; VA Information Resource Center, 2018). There were 462,672 (14%) veterans who died at some point during the study period. I removed 790,633 person-year records for the years after a person died. The final sample had 3,252,982 veterans and 17,624,182 person-year observations.

3. Measures

a. Outcome

Weight and height were obtained from patient-level encounters (Zenk et al., 2018). An annual BMI measurement was calculated from measured height (the modal value across all years of data) and the mean of all outpatient weight measurements in the second half of each calendar year (if none, weights from the first half of the year were used) (Zenk et al., 2018). Years with no weight measurement had missing values (no imputation) for the outcome and thus did not contribute to the model estimation.

b. Independent variable of interest

Mobility limitation was a binary variable based on a model developed by Shumway-Cook and colleagues (Shumway-Cook et al., 2005). In chapter 1, I developed a mobility limitation algorithm using data for a subset of veterans who had also participated in the Medicare Current Beneficiary Survey (MCBS) as a development dataset. That dataset included self-reported difficulty walking and difficulty walking a quarter mile. To predict a veteran's self-reported mobility limitation (modeled as dichotomous), I used healthcare administrative data on assistive mobility device use, health conditions related to mobility limitations, demographics, and healthcare utilization. The predictive model had a high Area Under the Curve (AUC) (0.80), which means that the model did well at distinguishing between those with and without a mobility limitation. It also had a high sensitivity (70%), meaning that the algorithm correctly identified a large percentage of those with mobility limitations and a high specificity (79%), meaning that the algorithm also did well at ruling out people who did not have a mobility limitation. I made one modification to the algorithm by removing the BMI predictor because in this study, BMI is the outcome. The equation and coefficients used in this analysis were

(2): y*moblim* = -1.42constant + 3.15*homemod* + 2.06*copd* + 1.88*wheelchair* + 1.53*orthpros* + 1.15*cns* + 1.10*gait* + 0.84*division* + 0.82*depression* + 0.81*pvd* + 0.64*musculoskeletal* + 0.53*diabetes* + 0.38*prioritygroup*

Where y*moblim* is the predicted binary outcome (0-1) for having a mobility limitation, the constant is the intercept; *homemod* is home modifications, such as ramps and lifts; *copd* is Chronic Obstructive Pulmonary Disease; *wheelchair* is receipt of a manual or power wheelchair; *orthpros* is receipt of orthotics or prosthetic devices for walking; *cns* is diseases of the central nervous system; *gait* is abnormalities of gait or diagnosis of difficulty walking; *division* is being in census division seven (West South Central); *depression* is diagnosed with clinical depression; *pvd* is peripheral vascular disease; *musculoskeletal* is having a diagnosis for a condition related to the musculoskeletal system or connective tissue; *diabetes* is having a diagnosis for diabetes mellitus with or without complications; and *priority group* is being in priority group 1, which is related to a service-connected disability or being 'home-bound'. The model was estimated using a logistic regression model. Predicted values for mobility limitation were then calculated based on estimation results (coefficients shown in equation (2)) for each year of the data for the full WAVES sample. Predicted values ranged from 0-1.

To create the binary variable indicating a veteran has a mobility limitation, it is necessary to establish a cut-off point whereby those above the cut-off are coded as having a mobility limitation and those below the cut-off are coded as having no mobility limitation. I chose to use a cut-off of 0.412, which was the point on the receiver operator curve that minimizes false positives and false negatives, also called Youden's index (Youden, 1950). This, in turn, maximizes sensitivity and specificity. If one of the variables in the mobility limitation algorithm was missing for a particular year, the mobility limitation variable was not calculated for that year. However, there were no missing values for the variables used in the algorithm.

Regressing BMI on mobility limitation in the same year suffers from the problem of reverse causality of obesity causing a mobility limitation. The estimated effect captures both the effect of mobility limitation on BMI and the effect of a high BMI that leads to a mobility limitation. To address this issue, I used a lagged mobility limitation variable that estimated the effect of having a mobility limitation in the previous year on BMI in the current year. The lag strengthened our argument that the change in BMI reflected the effect of mobility limitation and did not also reflect the effect of BMI on mobility limitation. The disadvantage was that in using this approach, one year of data were lost. So only the subject's second year until their last year of data from WAVES were used, for a maximum of six years.

c. <u>Stratification variables</u>

I used a gender variable to run separate models for men and women. This is common practice in assessing body weight outcomes because there are different average trajectories of BMI for males and females (Jackson et al., 2002; Wang & Beydoun, 2007). Additionally, the sample in WAVES was mostly male and so if combined, the results would mostly reflect that of males. Given that this gender disproportionality is one of the key observed areas that the VA sample differs from the general population, running separate models is important to avoid generalizability to the full population. I developed three series of categorical variables for age, comorbidity, and baseline weight status to stratify my analysis. Age category dummy variables were for ages 20 to 39, 40-49, 50-64, 65-74, and 75+. These related to young, middle age, older middle age, older age, and very old age respectively.

Several comorbidity indices exist for studying comorbidity in healthcare administrative data and which weight diseases based on severity and likelihood of mortality. The Charlson Comorbidity Index was developed in 1987 to predict risk of inpatient mortality and used a set of 17 chronic conditions (Charlson, Pompei, Ales, & MacKenzie, 1987). Quan et al updated the Charleson Comorbidity Index in 2011 with new weights that better reflected progress made on the life expectancy of certain diseases (AIDS) (Quan et al., 2011). The Charleson and Quan indices are used regularly in health services research studies on utilization (Yurkovich, Avina-Zubieta, Thomas, Gorenchtein, & Lacaille, 2015) and outcomes, such as mobility limitation (Wells, Williams, Kennedy, Sawyer, & Brown) as a way to control for subjects' co-occurring health conditions that are severe. In my study, it is important to control for comorbidities as they could be associated with BMI and mobility limitations. Related to severity of diseases, comorbidities can lead to weight loss as well as to mobility limitation (Forman-Hoffman et al., 2008). I calculated the comorbidity score based on weights developed by Quan et al. (2011). Similar to other studies, I collapsed the comorbidity score into three groups based on a score of 0, 1-3, and ≥ 4 representing none, some, and many comorbidities (Johnston et al., 2015; Yang, Chen, Hsu, Chang, & Lee, 2015).

The third stratification variable was veteran's baseline BMI category. BMI categories have been defined by the CDC as underweight <18.5, normal 18.5-24.9, overweight 25.0 – 29.9, class-1 obese 30 – 34.9, class-2 obese 25 – 39.9, and class-3 obese ≥40. (Centers for Disease Control and Prevention, 2017)

d. <u>Covariates</u>

I selected person-level covariates that I hypothesized could be correlated with both BMI and mobility limitation. I only used covariates that change over time because all time-invariant variables are omitted from any of the fixed-effects models. Marital status (married, single, widowed etc.) was included because being married is correlated with higher BMI (Klos & Sobal, 2013; Sobal, Rauschenbach, & Frongillo, 1992) and potentially with mobility limitation in cases where a veteran may have a partner who is also a caregiver (Pienta, Hayward, & Jenkins, 2000). I also included a variable on race/ethnicity in the pooled cross-sectional models

Being in a rural area may present additional barriers to people with mobility limitations, such as distance, access to transportation and other services, and lack of physical activity opportunities (Mulligan, Hale, Whitehead, & Baxter, 2012; Pierce, 1998). These factors associated with the experience of a mobility limitation in rural areas could affect food shopping and consumption patterns as well as physical activity, and thus affect BMI in a different way than for those in urban areas. To account for differences between urban and rural areas, I included a variable for metropolitan area as defined by the National Center on Health Statistics (NCHS) (Ingram & Franco, 2013). The metropolitan variable is coded at the county level and uses population and socio-economic variables to differentiate levels of urbanity.

As part of a natural dying process, people generally lose weight in the months prior to death (Alley et al., 2010). Because dying could be correlated with BMI and mobility limitation, I controlled for dying using death records available as part of the WAVES data. I developed two dummy variables to account for these unobserved aspects of the dying process, one for if a veteran died in that year, and another if they died in the first six months of the subsequent year, including in the year after the study period (2016).

I included three covariates representing health conditions that could change over time, and which could be correlated with both mobility limitation and change in BMI. As with the other health conditions already described, these were also identified through ICD9 diagnosis codes. I used two mental health conditions, substance abuse disorder, and depression. Sarcopenia, also known as deconditioning, is related to changes in muscle mass, which can lead to a mobility limitation as well as affect BMI by showing as decreased weight (St-Arnaud-McKenzie et al., 2010; Stajkovic, Aitken, & Holroyd-Leduc, 2011; Vahlberg, Zetterberg, Lindmark, Hellström, & Cederholm, 2016). Finally, I included stroke as a covariate because it is one of the leading causes of mobility limitation (Wesselhoff, Hanke, & Evans, 2018). Obesity is a risk factor for stroke, but a stroke can also impair swallowing function and lead to weight loss (Oesch, Tatlisumak, Arnold, & Sarikaya, 2017).

I included four variables on healthcare utilization. Having more hospital admissions may reflect acute health problems or a worsening health status that could affect both BMI and mobility limitation.

Additionally, length of stay is important to control for because longer stays in the hospital are associated with weight loss (de Luis et al., 2006; Kyle, Genton, & Pichard, 2005) and possible mobility limitation due to the severity of the health related event (Bodilsen et al., 2016). The number of primary care visits and the number of specialist visits were included because they may reflect an unobserved health problem affecting mobility limitation. These visits may also reflect treatment or rehabilitation that could affect both mobility limitation and BMI.

4. **Descriptive analysis**

I began by running descriptive statistics for all variables, such as frequencies, means, and standard deviations. I used the subjects' first year in the study. This was most often 2009, but was sometimes later for subjects who entered the study later. I examined correlations between each covariate to identify any potential collinearity. To provide some face validity to the mobility limitation predicted variable, I examined cross tabulations between health conditions known to be associated with mobility limitation and the predicted mobility limitation variable with the notion that mobility limitation should be prevalent in people with these conditions. If not, it would be an indication that the algorithm was likely not sufficiently sensitive. The health conditions included stroke, morbid obesity, paralysis, spinal cord injury, and osteoarthritis (Iezzoni, 2002). Additionally, I graphically examined the percentage of the sample predicted to have a mobility limitation in each year of the study across each of the five age groups. I examined the prevalence of obesity in the sample that had a mobility limitation compared to those without a mobility limitation in each year of the study. Lastly, in Table XXVI, Appendix B, I created a table showing differences between those in the MCBS sample used in chapter one with those eligible for Medicare in 2010, as well as between the MCBS sample and those not eligible for Medicare in 2010.

5. **Linear regressions**

I developed two models to compare approaches for studying the effect of mobility limitation on BMI. Since the outcome BMI is linear, and because this study was interested in understanding the magnitude of the effect of mobility limitation on BMI, I used Ordinary Least Squares (OLS) regressions—one pooled cross-sectional and one that used individual fixed effects.

I began by running a pooled cross-sectional model with year fixed effects to account for time trends. In this model, no adjustments were made for repeated years of data for the same individual. Doing so is treating the data as if it were from all different people and individual observations are independent. The equation for the pooled cross-sectional OLS regression is:

$$(3): BMI_{it} = \beta_0 + \beta_1 moblim_{it-1} + \beta_2 X_{it} + \delta_3 T_t + \varepsilon_{it}$$

Here, *BMI* is the outcome for the individual i in time period t.; β_0 is the year specific intercept. $\beta_1 moblim_{i-1t}$ is the binary lagged mobility limitation variable; $\beta_2 X_{it}$ is a vector of the covariates: Quan group, year, age group, substance abuse disorder, depression, sarcopenia, stroke, metro, marital status, hospital admission, length of stay, primary care encounters, specialist care encounters, and dying or dead in that year; $\delta_3 T_t$ is the year fixed effects, which capture secular trends, and ε_{it} is the error term. The limitation of this equation is that in order for it to meet the assumptions of OLS and obtain consistent, unbiased estimates of $\beta_1 moblim_{it-1}$, we must assume that ε_{it} is not correlated with $\beta_1 moblim_{it-1}$. This is a very difficult assumption to meet because there are many unobserved factors that threaten this assumption, such as income, education, race etc.

An approach to addressing this problem is to use a fixed-effects estimator. Wooldridge (2015) explains that the error term in equation (3) is made of two components a_i and $u_{it.}$ a_i is the unobserved time-invariant factors and u_{it} is the time varying error or idiosyncratic error. a_i is also called the fixed effect, meaning that it is ‘fixed’ over time. By including a_i (the fixed effect), we control for all time-invariant unobserved factors that might be correlated with mobility limitation and BMI. So factors such as gender, race, generally education level, genetic predispositions, family history of obesity etc. Although, the ability to control for all time-invariant unobserved/unmeasured factors is very powerful, the strict exogeneity assumption still applies, (Wooldridge, 2015) which in this case would be that we assume that u_{it} is uncorrelated with $\beta_1 moblim_{it-1}$. In other words, the assumption is that there are no time-varying omitted variables that are correlated with the error term. In longitudinal panel data, there is serial correlation between error terms in different years among observations for the same individual, which is a problem because it violates the OLS assumption that error terms across observations are not correlated. To control for this problem, I clustered the standard errors on the individual's study id to obtain cluster-robust standard errors in all the fixed-effects models (Wooldridge, 2015). In addition, because the mobility limitation variable is a predicted variable and includes some measurement error, I bootstrapped the standard errors for the mobility limitation variable using 500 repetitions (Davison & Hinkley, 1997; Guan, 2003). Equation (4) is for the fixed-effects model:

$$(4):\ BMI_{it} = \beta_0 + \beta_1 moblim_{it-1} + \beta_2 X_{it} + \delta_3 T_t + a_i + u_{it},\ t=1,2,..6$$

Here, *BMI* is the outcome for person *i* in time period *t*. β_0 is the year specific intercept; $moblim_{it-1}$ is the lagged mobility limitation predictor of interest; X_{it} is a vector of covariates for Quan group, year, age group, substance abuse disorder, depression, sarcopenia, stroke, metro, marital status, hospital admission, length of stay, primary care encounters, specialist care encounters, and dying or dead in that year; T_t is the year –fixed effects that control for unobserved time trends; a_i is the 'fixed effect' or time-invariant factors, and u_{it} is the time-varying or idiosyncratic error. I apply equation (4) to all the subgroup and sensitivity analyses.

6. **Subgroup analysis**

I stratified my analysis to identify which subgroups are more at risk for increased BMI as a result of a mobility limitation. I conducted separate models for the five age groups at baseline, the three groups of comorbidity based on the baseline Quan score, and the six baseline weight categories. In the models stratified by Quan groups, I controlled for possible increases in comorbidities from baseline by adding a continuous variable for the raw Quan scores. I tested for significance of difference in levels of age and comorbidity by including an interaction term with the mobility limitation variable in the full (non-stratified) models. This was not possible with baseline weight status because it does not vary over time.

7. **Sensitivity analyses**

I conducted five sensitivity analyses to test alternative forms of the mobility limitation predictor as well as potential threats of confounding variables. First, I tested how sensitive the results were to changes in the method I used to classify veterans as having a mobility limitation or not. From the predictive model of mobility limitation, I generated predicted probabilities that range from 0-1 and which required a cut-off to be established to classify mobility limitation as a binary variable. Instead of using the cut-off value that corresponded to the maximization of sensitivity and specificity, I changed the cut-off point by a value that represented a 5% increase in specificity from the original mobility limitation algorithm. So those above the value of 0.445 were now coded as having a mobility limitation and those below that value were coded as not having a mobility limitation. Increasing the specificity means that there are fewer false positives and more false negatives. So, less of the total sample was characterized as having a mobility limitation.

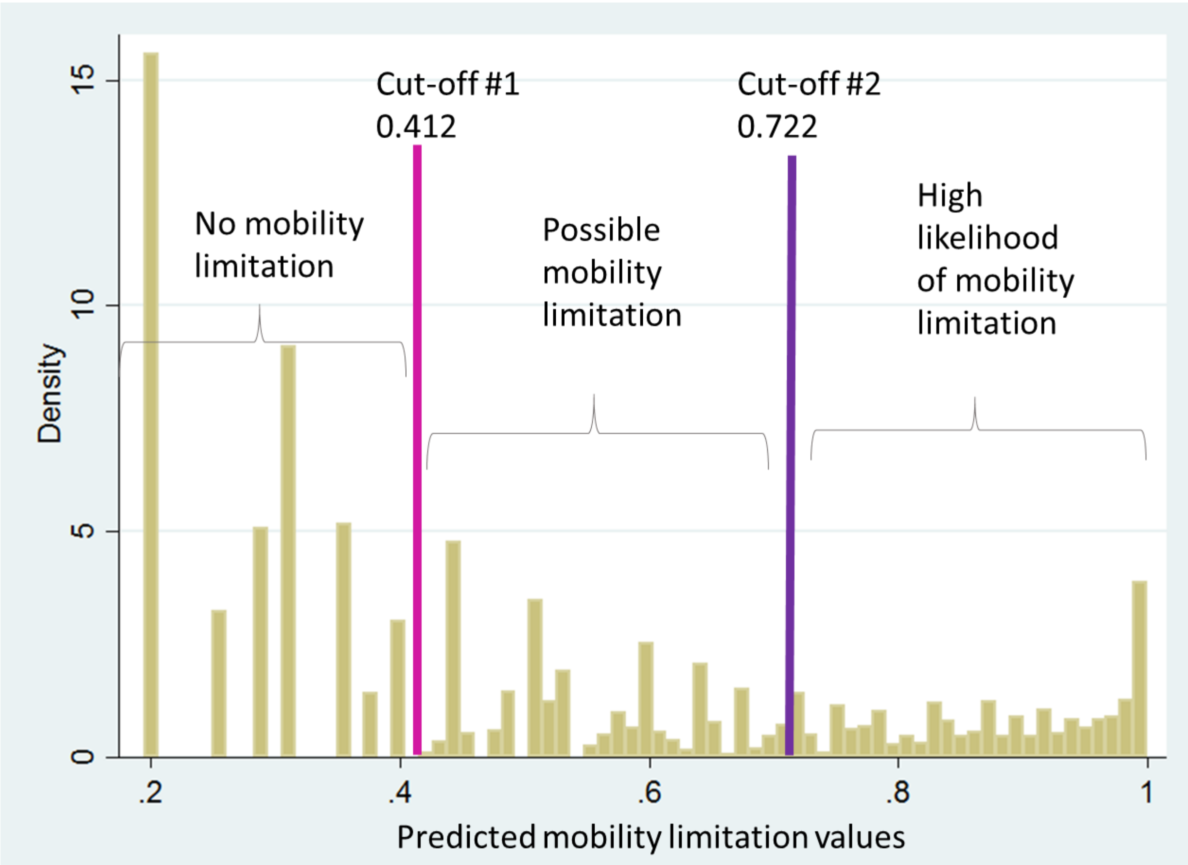
Individuals with more severe mobility limitations, such as those with SCI or quadriplegia, are more likely to have inaccurate weight measurement due to lack of weight scales and inaccurate weight measuring procedures (Locatelli & LaVela, 2016). I tested whether controlling for veterans with SCI by including a dummy variable for having SCI affected results. I also tested a model excluding veterans with quadriplegia or paraplegia. I tested whether modifying the Quan comorbidity index was necessary because similar predictors were used in the mobility limitation algorithm. The modified version removed variables that I had also included in the mobility limitation algorithm. These included COPD, diabetes with complications, and rheumatism. People often think of those with mobility limitations as individuals who use wheelchairs (Iezzoni, 2002). To consider this simple approach, I tested whether using a variable for individuals in wheelchairs had similar results to models that used mobility limitation as the main predictor of interest.

In order to address the possibility for over-sensitivity of the mobility limitation algorithm, I also developed a categorical mobility limitation variable. I started with the original binary mobility limitation variable. I created a second binary variable with a higher cut-off that was based on a specificity of 95% as identified through the analysis in chapter one. Those above 0.722 were coded as having a mobility limitation (compared to the previous cut-off of 0.412). This group is essentially those with a high likelihood of having a mobility limitation. I combined the original binary variable with the high specificity binary variable using the logic that those classified as not having a mobility limitation by the original variable were coded as (0), those classified as having a mobility limitation in the original binary variable only were coded as (1) and those classified as having a mobility limitation variable in both the original binary and high specificity binary variables were coded as (2). Figure 5 illustrates the distribution of predicted values from 0-1, the location of each cut-off and who was coded as each category. Essentially, these three categories represent (0) high likelihood of not having a mobility limitation, (1) possible mobility limitation, and (2) high likelihood of having a mobility limitation. Finally, as an additional analysis, I examined a pooled cross-sectional quantile regression instead of a linear regression. The methods and results for the quantile regression are included in Table XXVIII, Appendix B.

D. Results

In Table IX, I summarized the characteristics of the sample. Based on the predicted mobility limitation variable, 34.8% of male veterans had a mobility limitation. The average BMI for males was 29.9 (SD 5.8) , just below the threshold of what is considered obese (BMI≥30). Only 17.6% of males were of normal weight; 44% of males were obese, and the largest percentage (27%) was in class-1 obese (BMI of 30-35 kg/m^2). The male sample was mostly older age (84.1% above age 50), white (69%), and married (58%). Most males (53%) had no comorbidities from the Quan comorbidity index; 39.3% had Quan score between 1-3, and 7.6% had a Quan score of ≥4. Some males were diagnosed with depression (23%), substance abuse disorder (13.5%), sarcopenia (0.2%), and stroke (3.7%). Most males lived in metropolitan counties (77%). The mean hospital admissions was 0.1 (SD 0.5); the mean length of stay was 1.0 days (SD 6.4); the mean number of primary care visits was 2.9 (SD 2.6), and the mean number of specialist visits was 4.7 (SD 7.7).

Figure 5: Distribution of Predicted Mobility Limitation Values and Cut-offs Used for the Alternative Categorical Mobility Limitation Variable [a,b,c]



[a]The values in the histogram are the values that were predicted after a logistic regression was run for the sample in chapter one of this dissertation.

[b]Cut-off#1 is used for the original binary mobility limitation variable.

[c]Cut-off #2 is for the sensitivity analysis and represents a 95% specificity for the algorithm developed in chapter one of this dissertation.

Among female veterans, 37.7% were predicted to have a mobility limitation at baseline. The average BMI for females was 29.8 (SD 6.5). A quarter of females were of normal weight; 45% of females were obese and most of those (30.6%) were in the class-1 obese category (BMI of 30-35 kg/m^2). The female sample was mostly younger age (90% below age 65), white (55%), and not married (65%). Most females (73.5%) had no comorbidities from the Quan comorbidity index; 24.3% had Quan score between

1-3, and only 2.3% had a Quan score of ≥4. Many females were diagnosed with depression (41.0%), and some with substance abuse disorder (9.0%), sarcopenia (0.1%), and stroke (1.3%). Most females lived in metropolitan counties (83.6%). The mean hospital admissions was 0.11 (SD 0.49); the mean length of stay was 0.83 days (SD 5.64); the mean number of primary care visits was 3.2 (SD 2.8), and the mean number of specialist visits was 6.3 (SD 9.2).

Figure 6 summarizes the percentage of veterans with a mobility limitation in each year of the study for ages 20-39, 40 to 49, 50 to 64, 65 to 74, and 75+. The percentage of veterans with a mobility limitation overall increased from 35% in 2009 to 61% in 2015. For those ages 20 to 39, the magnitude is smaller, going from 24% to 46%. Although these rates may be considered high, a study that compared objective measures with self-reporting found that older adults significantly under-reported their ability to walk a quarter mile (Simonsick et al., 2008). The baseline value identified is within the range of other studies and datasets. Shumway-Cook et al. (2005) estimated that 47% of Medicare recipients had a mobility limitation (mild-to-severe). Based on data I downloaded from NHIS for the years 2010-2017, 30% of veterans reported having difficulty walking a quarter mile (Lynn A. Blewett, 2018). There are no data available from studies that followed the same cohort over time and reported how rates of mobility limitation changed. Another reason the rates may be increasing is that they do not reflect all veterans but veterans who use the VHA. In 2014, an estimated 42% of all veterans were enrolled in the VA healthcare, and between 63% - 65% of those enrolled actually used VA healthcare (Bagalman, 2014). VHA users are more likely to be lower income, unemployed, older and have lower health status (Liu, Maciejewski, & Sales, 2005; Nelson, Starkebaum, & Reiber, 2007), all of which may combine to suggest reasons for the higher rates of mobility limitation found here. Lastly, because the VHA benefits for assistive mobility devices are better than Medicare benefits (Hubbard Winkler et al., 2006), the higher rates may reflect that fact that veterans are choosing to use VHA services for mobility devices once they need them. The larger slope from the baseline year to the second year may reflect missing data from the initial year.

TABLE IX: CHARACTERISTICS OF THE STUDY SAMPLE IN THE BASELINE YEAR OF THE WEIGHT AND VETERANS ENVIRONMENTS STUDY (WAVES) 2009-2014[a]

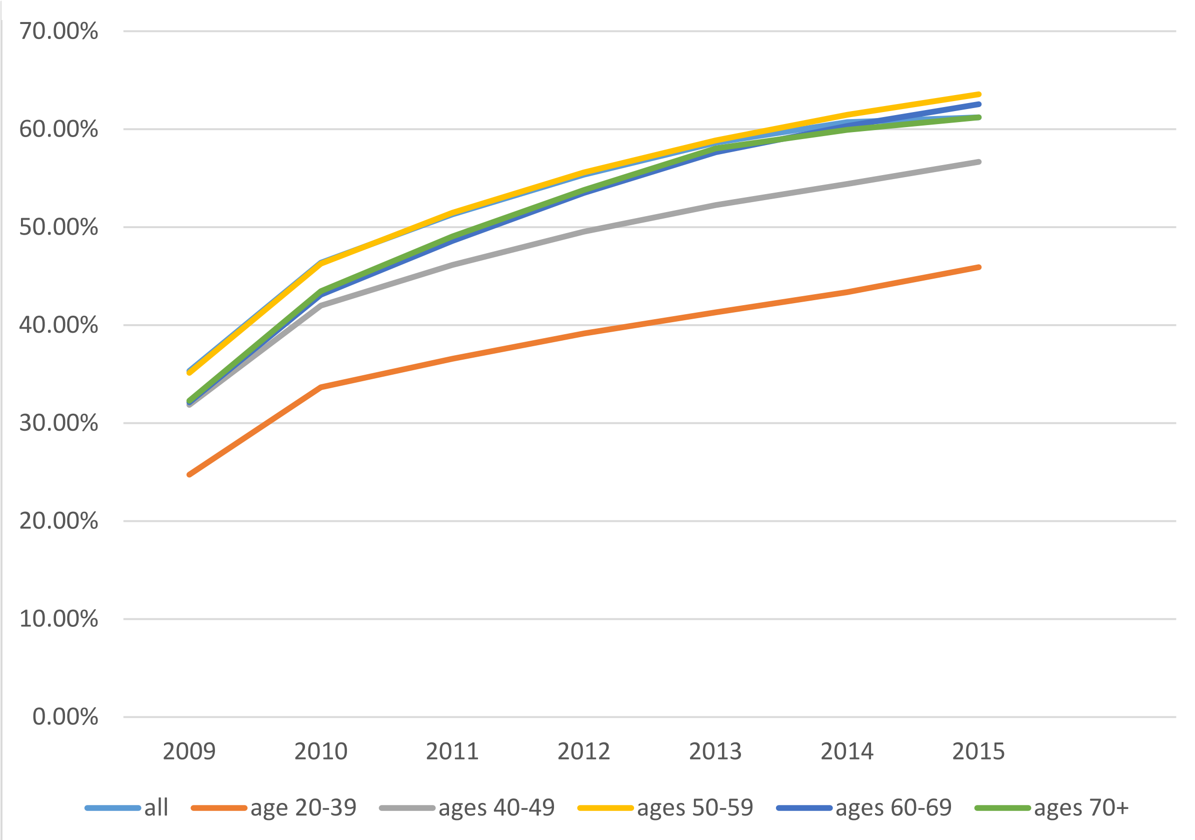
	Male (*n* = 3,037,627)	**Female** (n = 225,679)
Variable	**%**	**%**
Body Mass Index (*M and SD*)	29.9 (5.8)	29.8 (6.5)
Mobility limitation[b]	34.8	37.7
Underweight	0.8	1.2
Normal weight	17.6	23.6
Over weight	37.4	30.6
Class-1 obese	27.2	24.4
Class-2 obese	11.3	12.9
Class-3 obese	5.7	7.3
Age 20-39	7.6	30.0
Age 40-49	8.3	23.4
Age 50-64	40.2	36.7
Age 65-74	26.8	7.0
Age 75+	17.1	2.9
Unknown marital status	0.7	1.1
Married	58.2	34.0
Separated/divorced	22.9	32.9
Widowed	4.4	4.2
Single	13.8	27.8
Non-Hispanic White	68.6	55.4
Non-Hispanic Black	15.8	28.6
Hispanic	4.1	5.1
Other	2.0	3.1
Unknown	9.4	7.8
No comorbidity[c]	53.0	73.5
Comorbidity score of 1-3	39.3	24.3
Greater than 4 comorbidity score	7.6	2.3
Quan Comorbidity score (*M and SD*)	1.0 (1.6)	0.4 (1.0)
Depression	23.7	41.0
Substance abuse disorder	13.5	9.0
Sarcopenia	0.2	0.1
Stroke	3.7	1.3
Metro	77.0	83.6
Hospital admissions (*M and SD*)	0.1 (0.5)	0.1 (0.4)
Length of stay (*M and SD*)	1.0 (6.4)	0.8 (5.5)
# of primary care encounters (*M and SD*)	2.9 (2.6)	3.2 (2.8)
# of specialist encounters (*M and SD*)	4.7 (7.7)	6.3 (9.2)

[a] Data from WAVES come from Veteran's Health Administration Corporate Data Warehouse.

[b] Mobility limitation was predicted using a mobility limitation algorithm.

[c] Comorbidity score was generated from the Quan Comorbidity Index (Quan et al., 2011).

Figure 6: Percent of Veterans with a Mobility Limitation in the Weight and Veterans Environments Study by Age Group, 2009-2015



[a] Mobility limitation was predicted using a mobility limitation algorithm.

Table X shows the number and percentage of people in WAVES who were predicted to have a mobility limitation and also have health conditions known to be related to mobility limitation. In the baseline year of the study, 68.9% of those with cerebrovascular disease were predicted to have a mobility limitation; 70.4% with osteoarthritis had a mobility limitation; 93.9% of those with quadriplegia or paraplegia had a mobility limitation, and 61.7% with morbid obesity had difficulty walking. The percentage with morbid obesity that have a mobility limitation may be seen as lower than expected. However, this is likely because we removed BMI from the mobility limitation algorithm. Although we might expect that one hundred percent of those with quadriplegia and paraplegia would have a mobility limitation, the codes used for those conditions have not been validated, and so there is a degree of uncertainty about whether those individuals have those conditions. Additionally, we expect some false negatives to be associated with using the algorithm.

TABLE X: FREQUENCY OF MOBILITY LIMITATION PREDICTED AMONG VETERANS WITH HEALTH CONDITIONS OFTEN ACCOMPANIED BY A MOBILITY LIMITATION IN THE BASELINE YEAR OF THE WEIGHT AND VETERAN'S ENVIRONMENT STUDY [a]

Health condition	**Number with a mobility limitation**	**Percentage with a mobility limitation (%)**
Cerebral Vascular Disease	154,807	68.9
Osteoarthritis	369,967	70.4
Quadriplegia/paraplegia	10,366	93.9
Morbid obesity	102,495	61.7

[a] Health conditions were identified through ICD9 diagnosis codes.

In Table XI, I compare the rate of obesity between those with and without a mobility limitation. The percentage of obese veterans is higher among those with a mobility limitation in 2009 (49.1% vs. 41.0%) and in subsequent years as well. The percentage of obesity for both groups decreases, and this may reflect the fact that the sample is predominantly older age veterans who may be at the stage of life when they are losing weight.

The pooled cross-sectional OLS regression and fixed-effects regression results are shown in Table XII and are described separately for males and females below:

1. **Results of regression models for males**

Based on pooled cross-sectional models, there was a 1.120 unit increase in BMI ($p<0.001$) for males who obtain a mobility limitation. In fixed-effects models, the effect of a mobility limitation was substantially lower at only a 0.043 unit increase in BMI ($p<0.001$). Increases in the Quan comorbidity score were associated with increases in BMI in the pooled cross-sectional model, but with decreases in

TABLE XI: PREVALENCE OF OBESITY AMONG VETERANS BY MOBILITY LIMITATION STATUS FOR VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENTS STUDY 2009-2015

	Mobility limitation		**No mobility limitation**	
	Number obese	% obese	Number obese	% obese
2009	459,225	49.1%	702,830	41.0%
2010	599,453	48.4%	552,010	39.9%
2011	649,622	48.0%	484,168	39.4%
2012	684,673	47.7%	430,120	38.9%
2013	712,887	47.5%	391,562	38.7%
2014	732,627	47.6%	367,254	38.5%
2015	718,691	47.8%	325,508	38.4%

BMI in the fixed-effects model. For instance, in males who had many (greater than 4) comorbidities, the effect on BMI is a 0.895 unit increase ($p<0.001$) in the pooled cross-sectional model, but was a 0.597 unit decrease in BMI ($p<0.001$). Increases in age group compared to those who were 20-39 was associated with increases in BMI for all age groups. The effect was strongest for ages 65-74 (0.971 BMI units, $p<0.001$) and lowest for ages 40-49 (0.595 BMI units, $p<0.001$). Based on the year fixed effects, males are decreasing in BMI over time as all the effects were negative and became larger in each year, going from -0.056 BMI units ($p<0.001$) in 2011 to -0.297 BMI units ($p<0.001$)in 2015..

In terms of the other covariates in the model, being unmarried (separated/divorced, widowed, single, or unknown marital status) compared to being married were all associated with a decrease in BMI. Depression and substance abuse disorder were associated with an increase in BMI. The four healthcare utilization variables were associated with a decrease in BMI, except for primary care encounters, which was associated with a very small increase. Living in a metropolitan area was associated with a decrease in BMI. Dying in the following year or in the current year were both associated with large decreases in BMI. Being diagnosed with sarcopenia or stroke were associated with a decrease in BMI. The pooled cross-sectional models show that compared to being non-Hispanic white, being non-Hispanic black was associated with a decrease in BMI; being Hispanic was associated with an increase in BMI, and being other race or unknown race was associated with a decrease in BMI.

2. **Results of regression models for females**

Based on pooled cross-sectional models, there was a 1.102 unit increase in BMI ($p<0.001$) for females with a mobility limitation. In fixed-effects models, the effect of a mobility limitation was substantially lower at only a 0.104 unit increase for females ($p<0.001$). For females with many (greater than 4) comorbidities, the effect on BMI was a 1.005 unit increase ($p<0.001$) in the pooled cross-sectional model, but was a 0.940 unit decrease in BMI ($p<0.001$) in fixed-effects models. Increases in age group compared to those who were 20-39 was associated with increases in BMI up to 64. For instance, age group 40-49 was associated with an increase of 0.422 BMI units ($p<0.001$). At age group 65-74, mobility limitation was associated with decreases in BMI. For instance, age group 75-86 was associated with a decrease of 0.786 BMI units ($p<0.001$). Based on the year fixed effects, females are increasing in BMI, as the year effect goes from 0.050 BMI units ($p<0.001$) in 2011 to 0.394 BMI units ($p<0.001$) in 2015.

In terms of the other covariates in the fixed-effects model, being unmarried (separated/divorced, widowed, single, or unknown marital status) compared to being married were all associated with a decrease in BMI. Depression was associated with an increase in BMI for females, but substance abuse disorder was not associated with BMI for females. Hospital admissions and length of stay were associated with decreases in BMI. Primary care encounters and specialist encounters were associated with a small increase in BMI. Living in a metropolitan area was not significantly associated with BMI for females. Dying in the following year or in the current year were both associated with large decreases in BMI. Being diagnosed with sarcopenia or stroke were associated with a decrease in BMI. The pooled cross-sectional models show that compared to being non-Hispanic white, being non-Hispanic black was associated with an increase in BMI; being Hispanic was not associated with BMI; being other race was associated with a decrease in BMI, and having unknown race was associated with an increase in BMI.

TABLE XII: RESULTS FROM REGRESSION MODELS OF BMI REGRESSED ON MOBILITY LIMITATION ADJUSTING FOR INDIVIDUAL AND YEAR FIXED EFFECTS AND TIME-VARYING COVARIATES FOR VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY 2009-2015 [a,b]

	Male, N= 13,381,684		Female, N= 989,516	
	Pooled cross-sectional	**Fixed Effects**	**Pooled cross-sectional**	**Fixed Effects**
Mobility limitation[c]	1.120***	0.043***	1.102***	0.104***
	(0.004)	(0.002)	(0.017)	(0.011)
Quan comorbidity score (ref=no comorbidities)				
Quan score 1-3	0.650***	-0.061***	1.002***	-0.158***
	(0.007)	(0.003)	(0.034)	(0.017)
Quan score >=4	0.895***	-0.597***	1.005***	-0.940***
	(0.013)	(0.006)	(0.089)	(0.046)
Age groups (ref = age 20-39)				
age 40-49	1.323***	0.595***	1.345***	0.339***
	(0.018)	(0.010)	(0.038)	(0.022)
age 50-64	0.118***	0.942***	1.215***	0.422***
	(0.015)	(0.012)	(0.037)	(0.028)
age 65-74	-0.777***	0.971***	0.855***	-0.018
	(0.015)	(0.012)	(0.056)	(0.035)
age 75-86	-2.842***	0.710***	-1.213***	-0.786***
	(0.016)	(0.013)	(0.076)	(0.048)
Year fixed effects (ref = 2010)				
2011	-0.067***	-0.056***	-0.126***	0.050***
	(0.002)	(0.001)	(0.010)	(0.006)
2012	-0.060***	-0.125***	-0.138***	0.090***
	(0.003)	(0.002)	(0.012)	(0.007)
2013	-0.032***	-0.175***	-0.105***	0.166***
	(0.003)	(0.002)	(0.014)	(0.009)
2014	-0.008*	-0.229***	-0.056***	0.284***
	(0.004)	(0.002)	(0.015)	(0.010)
2015	-0.025***	-0.297***	0.008	0.389***
	(0.004)	(0.002)	(0.016)	(0.0107)
Marital Status (ref = Married)				
Separated/divorced	-0.718***	-0.062***	-0.030	-0.210***
	(0.009)	(0.007)	(0.035)	(0.024)
Widowed	-0.311***	-0.264***	0.310***	-0.471***
	(0.016)	(0.009)	(0.075)	(0.048)
Single	-0.932***	-0.168***	0.182***	-0.335***
	(0.011)	(0.008)	(0.037)	(0.028)
Unknown marital	-0.573***	-0.217***	-0.019	-0.290***

TABLE XII: RESULTS FROM REGRESSION MODELS OF BMI REGRESSED ON MOBILITY LIMITATION ADJUSTING FOR INDIVIDUAL AND YEAR FIXED EFFECTS AND TIME-VARYING COVARIATES FOR VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY 2009-2015 [a,b] (CONTINUED)

	Male, N= 13,381,684		Female, N= 989,516	
	Pooled cross-sectional	**Fixed Effects**	**Pooled cross-sectional**	**Fixed Effects**
	(0.044)	(0.018)	(0.132)	(0.065)
Health conditions and healthcare utilization				
Depression	-0.008	0.062***	0.307***	0.209***
	(0.009)	(0.005)	(0.033)	(0.018)
Substance Abuse Disorder	-2.034***	0.116***	-1.876***	0.043
	(0.010)	(0.006)	(0.046)	(0.031)
Hospital admissions	-0.343***	-0.222***	-0.156***	-0.203***
	(0.006)	(0.002)	(0.030)	(0.010)
Length of stay	-0.013***	-0.010***	0.0003	-0.008***
	(0.0004)	(0.0002)	(0.003)	(0.001)
Primary care encounter	0.142***	0.002***	0.124***	0.007***
	(0.001)	(0.0003)	(0.005)	(0.001)
Specialty care encounter	0.006***	-0.0008***	0.011***	0.001
	(0.0004)	(0.0001)	(0.002)	(0.001
Metropolitan area	-0.152***	-0.0104*	-0.430***	-0.009
	(0.008)	(0.004)	(0.038)	(0.016)
Died in following year	-1.560***	-0.736***	-1.756***	-0.783***
	(0.017)	(0.006)	(0.148)	(0.057)
Died in same year	-1.880***	-1.209***	-1.983***	-1.204***
	(0.014)	(0.006)	(0.115)	(0.055)
Sarcopenia	-0.642***	-0.576***	-0.079	-0.671***
	(0.053)	(0.025)	(0.323)	(0.153)
Stroke	-0.759***	-0.428***	-0.701***	-0.436***
	(0.015)	(0.009)	(0.105)	(0.063)
Race/ethnicity (ref = Non-Hispanic White)				
Non-Hispanic Black	-0.392***		1.216***	
	(0.010)		(0.034)	
Hispanic	0.034*		-0.009	
	(0.017)		(0.063)	
Other race	-0.540***		-0.501***	
	(0.025)		(0.086)	
Unknown race	-0.141***		0.059	
	(0.012)		(0.056)	
Constant	30.28***	29.42***	28.09***	29.93***

TABLE XII: RESULTS FROM REGRESSION MODELS OF BMI REGRESSED ON MOBILITY LIMITATION ADJUSTING FOR INDIVIDUAL AND YEAR FIXED EFFECTS AND TIME-VARYING COVARIATES FOR VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY 2009-2015 [a,b] (CONTINUED)

	Male, N= 13,381,684		Female, N= 989,516	
	Pooled cross-sectional	**Fixed Effects**	**Pooled cross-sectional**	**Fixed Effects**
	(0.016)	(0.012)	(0.049)	(0.029)
Adjusted R-squared	0.070	0.039	0.048	0.017

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

[a] Standard errors in parentheses, clustered on the subject and bootstrapped for the mobility limitation.

[b] Coefficients are reported from linear regressions with individual fixed effects.

[c] Mobility limitation is a predicted binary variable derived from a model in chapter one. The variable is lagged one-year.

3. **Sensitivity analyses results**

Table XIII summarizes the sensitivity analyses and compares each alternative model with the fixed-effects model shown above. The estimates from the fixed-effects model mostly held across sensitivity analyses. Using the alternate cut-off for females changed the estimated effect of mobility limitation from 0.104 to 0.073. The smaller effect makes sense in that changing the cut-off changes the cohort by reclassifying those with lower predicted values that were close to the cut-off as not having a mobility limitation. The lower effect on BMI indicates that those who were reclassified and have milder limitations may be driving some of the increase in BMI among all those with mobility limitation. There was only a small number of person-years with quadriplegia or paraplegia (55,025 for males and 2,936 for females), and so excluding these had no effect on the estimates. For the alternative approach of just estimating the effects for those who receive wheelchairs, wheelchairs were associated with a decrease in BMI. In an additional model looking at the effect of wheelchairs restricted to those under 40 (not shown here), wheelchairs had no effect on weight gain for males or females.

Table XIV compares the main findings of the pooled cross-sectional and fixed-effects regression models for the binary mobility limitation variable with findings from the alternative categorical mobility limitation variable that separated the sample into ‘no mobility limitation’, ‘possible mobility limitation’, and ‘high likelihood of mobility limitation’. There are two sets of results for the categorical variable with no mobility limitation as the reference. In pooled cross-sectional models, the effect of having a possible mobility limitation was 0.956 BMI unit increase ($p<0.001$) for males and 0.884 unit increase ($p<0.001$)for females, which were both lower than the effect of the binary mobility limitation variable (1.120 BMI unit increase ($p<0.001$) for males and 1.102 BMI unit increase ($p<0.001$) for females). In contrast, the effect for the high likelihood of a mobility limitation category was a 1.488 BMI unit increase ($p<0.001$) for males and 1.554 BMI unit increase ($p<0.001$) for females, which was higher than for the binary version. However, in fixed-effects models, the magnitude of the effects for possible mobility limitation and high likelihood of mobility limitation flip. The high likelihood of a mobility limitation category had the

TABLE XIII: SENSITIVITY ANALYSIS USING DIFFERENT APPROACHES TO ESTIMATE THE EFFECT OF MOBILITY LIMITATION ON BMI FOR VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY 2009-2015 [a,b]

	Male			**Female**		
Models	Coefficient	SE	person-year observations	Coefficient	SE	person-year observations
Mobility limitation[c] (from main fixed-effects model)	0.043***	(0.002)	13,381,684	0.104***	(0.011)	989,516
Sensitivity analyses						
Alternative cut-off[d]	0.043***	(0.002)	13,381,684	0.073***	(0.011)	989,516
Control for spinal cord injury[e]	0.044***	(0.002)	13,381,684	0.104***	(0.011)	989,516
Modified Quan comorbidity group[f]	0.044***	(0.002)	13,381,684	0.104***	(0.011)	989,516
Exclude quadriplegia or paraplegia[g]	0.044***	(0.002)	13,278,290	0.104***	(0.011)	985,325
Effect of wheelchairs instead of mobility limitation[h]	-0.208***	(0.007)	13,381,684	-0.171***	(0.028)	989,516

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

[a] Standard errors in parentheses, clustered on the subject.

[b] Coefficients are reported from linear regressions with person fixed effects controlling for the following covariates: Quan comorbidity group, year fixed effects, age group, substance abuse disorder, depression, sarcopenia, stroke, metro, marital status, hospital admission, length of stay, primary care encounters, specialist care encounters, and dying or dead in that year.

[c] Mobility limitation is a predicted binary variable derived from a model in chapter one. The variable is lagged one-year.

[d] A different cut-off was used that represented 5% higher specificity for creating a binary mobility limitation variable from a predicted model in chapter one.

[e] A dummy variable for Spinal Cord Injury was included.

[f] A modified Quan comorbidity grouping was used that removed variables that were also included in the mobility limitation algorithm.

[g] Excluded veterans with paraplegia or quadriplegia whose weight may be inaccurate based on ICD9 diagnosis codes.

[h] Instead of a mobility limitation variable, this model tested the effect of receiving a wheelchair.

smallest effect on BMI at an increase of only 0.0182 BMI units (p<0.001) for males and an increase of 0.0781 BMI unit increase (p<0.001) for females but the possible mobility limitation category had an increase of 0.048 BMI units (p<0.001) for males and 0.109 BMI unit increase for females (p<0.001). In fixed-effects models, the effects for possible mobility limitation were more similar in magnitude to the original binary mobility limitation variable, which was 0.043 BMI unit increase (p<0.001) for males and 0.104 BMI unit increase (p<0.001) for females. Based on analysis not shown here, the high likelihood of mobility limitation group is more obese as the rate of obesity was 50.2% compared to 46.9% for the possible mobility limitation group, and 39.7% for the no mobility limitation group. These proportions were significantly different at p<0.001.

TABLE XIV: SENSITIVITY ANALYSIS COMPARING OUTCOMES USING A BINARY MOBILITY LIMITATION VARIABLE VERSUS A CATEGORICAL MOBILITY LIMITATION VARIABLE IN REGRESSION MODELS OF THE EFFECT OF MOBILITY LIMITATION ON BMI FOR VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY, 2009-2014 [a,b,c]

	Male		Female	
	Pooled cross-sectional	Fixed Effects	Pooled cross-sectional	Fixed Effects
Mobility limitation (Binary)	1.120***	0.043***	1.102***	0.104***
SE	-0.004	-0.002	-0.017	-0.011
Mobility limitation (Categorical - ref:=No mobility limitation)				
Possible mobility limitation	0.956***	0.048***	0.884***	0.109***
	(0.007)	(0.002)	(0.031)	(0.011)
High likelihood of mobility limitation	1.488***	0.018***	1.554***	0.078***
	(0.010)	(0.004)	(0.040)	(0.015)

[a] Covariates used in the fixed-effects regression model of mobility limitation on BMI include: Quan Comorbidity group, age categories, year fixed effects, marital status, depression, substance abuse disorder, sarcopenia, stroke, hospitalization, length of stay, primary care visits, specialist care visits, died in following, and died in current year.

[b] Standard errors in parentheses, clustered on the subject.

[c] Mobility limitation is a predicted variable derived from a model in chapter one. The variable is lagged one-year.

4. **Stratified analyses results**

Table XV summarizes the effect of mobility limitation across different age groups, comorbidities, and baseline weight status. In younger age groups, there is a strong positive association between mobility limitation and BMI. There was an increase in BMI for veterans aged 20-39 (0.087 BMI units BMI units ($p<0.001$) for males and 0.104 BMI units ($p<0.001$) for females), 40-49 (0.070 BMI units ($p<0.001$) for males and 0.102 BMI units for females ($p<0.001$)), 50-64 (0.044 BMI units ($p<0.001$) for males and 0.056 BMI units ($p<0.01$) for females), and 65-74 (0.014 BMI units ($p<0.01$) for males), but no significant effect on BMI for females 65-74 and males or females ages 75 years and older. In the full model that included an interaction between mobility limitation and age group (see Table XXVIII, Appendix B), there was a significant effect of mobility limitation on BMI among those 20-39 and then decreasing effect that turns negative among each older age group. For each age group, the effect of mobility limitation was significantly lower than the reference group (ages 20-39).

In males, there was a small positive effect of mobility limitation on BMI among those with no comorbidities and some comorbidities (0.040 BMI units ($p<0.001$) and 0.037 BMI units ($p<0.001$) respectively). There was a larger effect among those with a many comorbidities (0.073 BMI units ($p<0.001$)). There is a similar pattern but larger in magnitude for females. In the full model that used an interaction between mobility limitation and Quan group (see Table XXVIII, Appendix B), having no comorbidities was associated with a increase in BMI, some comorbidities with no change, and many comorbidities with a decrease in BMI. The some and many comorbidities categories were significantly different from the reference group (no comorbidities).

Looking across baseline weight status categories, the effect of mobility limitation on BMI was largest among males who began in the underweight BMI category (0.133 BMI unit increase ($p<0.001$)). The category with the next highest increase in BMI was normal weight at 0.067 unit increase ($p<0.001$). The lowest effect for males was seen in those in obese class-1 (BMI 30-35), who had a 0.038 unit increase ($p<0.001$). The largest effect of mobility limitation on BMI for females was also for those who began in the underweight BMI category (0.186 BMI unit increase ($p<0.05$)). For females, the second

TABLE XV: THE EFFECT OF MOBILITY LIMITATION ON BMI USING FIXED-EFFECTS REGRESSION MODELS STRATIFIED BY AGE GROUP, COMORBIDITY, AND BASELINE WEIGHT STATUS FOR VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY 2009-2015 [a]

	Male			Female		
	Coefficient	SE	person-year observations	Coefficient	SE	person-year observations
Mobility limitation[b] (from main fixed-effects model)	0.043***	(0.002)	13,381,684	0.104***	(0.011)	989,516
Baseline age group						
Age 20-39	0.087***	(0.010)	949,448	0.104***	(0.020)	287,710
Age 40-49	0.070***	(0.008)	1,205,733	0.102***	(0.021)	250,039
Age 50-64	0.044***	(0.004)	5,985,980	0.056**	(0.018)	361,571
Age 65-74	0.014**	(0.005)	3,317,554	0.049	(0.040)	65,414
Age 75+	-0.001	(0.005)	1,874,600	0.102	(0.060)	23,527
Baseline comorbidity level[c]						
No comorbidity	0.040***	(0.004)	6,032,944	0.086***	(0.013)	647,547
Some comorbidity	0.037***	(0.003)	5,978,491	0.078***	(0.021)	308,018
Many comorbidities	0.073***	(0.020)	1,321,880	0.179*	(0.086)	32,696
Baseline weight class[d]						
Underweight	0.133***	(0.026)	68,237	0.186*	(0.073)	10,280
Normal weight	0.067***	(0.005)	2,182,967	0.095***	(0.018)	231,472
Over weight	0.046***	(0.003)	5,075,833	0.123***	(0.018)	303,080
Obese Class1	0.038***	(0.004)	3,732,612	0.112***	(0.022)	241,788
Obese Class2	0.040***	(0.008)	1,522,109	0.064	(0.034)	129,187
Obese Class3	0.051**	(0.017)	751,557	0.134*	(0.058)	72,454

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

[a] Coefficients are reported from linear regressions with individual-fixed effects controlling for the following covariates: Quan comorbidity group, year fixed effects, age group, substance abuse disorder, depression, sarcopenia, stroke, metro, marital status, hospital admission, length of stay, primary care encounters, specialist care encounters, and dying or dead in that year.

[b] Mobility limitation is a predicted binary variable derived from a model in chapter one. The variable is lagged one-year.

[c] Based on Quan comorbidity index (Quan et al., 2011).

[d] Defined by the CDC as underweight: <18.5, normal weight: 18.5-24.9, overweight 25.0 – 29.9, class-1 obese: 30 – 34.9, class-2 obese: 25 – 39.9 and class-3 obese: ≥40. (Centers for Disease Control and Prevention, 2017).

largest effect was seen in those who were in class-3 obese at baseline (0.134 BMI unit increase ($p<0.05$)). The effect in the other baseline weight categories was slightly smaller, except for class-2 obese, which was considerably smaller (0.064) and no longer statistically significant.

E. Discussion

Although numerous studies have documented a higher prevalence of obesity among people with mobility limitations compared to those without (An et al., 2015; Froehlich-Grobe et al., 2013; Rasch et al., 2008; Reichard et al., 2011; Weil et al., 2002), there is minimal research that has estimated the effect of mobility limitation on BMI. The purpose of this study was to examine the effect of mobility limitation on BMI in order to understand if people with mobility limitations are at higher risk for weight gain compared to those without mobility limitations. I conducted stratified analysis to explore how the effect of mobility limitation varies by age, comorbidity, and baseline weight status and to identify whether some groups are affected by mobility limitations more than other groups. In pooled cross-sectional models, I found a strong correlation between mobility limitation and increased BMI. Based on the pooled cross-sectional models, we would predict a mobility limitation to lead to a 7.6 pound weight increase for a 5-foot 10-inch male and a 6.5 pound weight increase for a 5-foot 5-inch female. However, in fixed-effects models that control for unmeasured time-invariant individual factors, I found that developing a mobility limitation had a small impact on BMI, at only about 0.29 pound increase for males and a 0.61 pound increase for females. Under the assumption that there were no time-varying omitted variables that were correlated with mobility limitation and BMI, these estimates can be interpreted as causal effects.

1. Contribution and strengths

To my knowledge, this is the first study to provide an estimate of the causal effect of mobility limitation on BMI. These findings imply that the high prevalence of obesity among people with mobility limitations is not driven by mobility limitation causing increases in weight, but by other unobserved/unmeasured factors that also impact people without disabilities, but that do not change over time and thus were controlled for in the fixed-effects models used in this study. The strength of this longitudinal study was that the fixed-effects models estimated the effect of mobility limitation controlling for the average change in BMI over time among veterans had they not had a mobility limitation. The fixed-effects strategy controls for all time-invariant unobserved factors that may be associated with mobility limitation and BMI by including a ‘fixed effect’ in the model estimation representing the time-invariant factors. Additionally, I included several time-varying factors from healthcare administrative data that are known to be associated with mobility limitation and BMI. No previous research has estimated an effect of mobility limitation on BMI with a strategy to address threats to causal interpretation.

Although the models that included individual fixed effects accounted for all time-invariant unobserved variables, there may be time-varying unobserved variables that could be correlated with mobility limitation and obesity, which would violate the strict exogeneity assumption that must hold in order to interpret the results as causal (Wooldridge, 2015). Some of the largest threats to internal validity are changes in an individual’s income, medications, employment, risk-taking behavior, and healthcare from other public or private insurers. Data on these factors were not available within the WAVES dataset, but it is important to understand how they might threaten our interpretation of the findings in this study.

Individual income may be an important unmeasured variable, as higher income is associated with physical activity, weight change, where people live, and healthcare coverage—all of which can be associated with mobility limitation and BMI. Although we used individual fixed-effects models, a change in individual-level income, which we were not able to observe, would threaten the internal validity. That is, a reduction in income could be the result of a mobility limitation but also affect an individual’s eating habits. Additionally, being unemployed and having a mobility limitation could lead to more sedentary behavior and an increase in BMI.

Another potential time-varying factor that threatens internal validity is change in medications. If someone were prescribed a certain medication associated with mobility limitation whose list of side effects includes weight gain, this would not be controlled for. Certain psychotropic medications are known to cause weight gain, and if people with mobility limitations are more likely to be prescribed such medications, this could bias the results.

A change in an individual's risk-taking behavior is an example of a factor that is unobservable in most studies, especially those using data from healthcare administrative sources. Various life events can shift an individual's risk-taking behavior and that change can be associated with developing a mobility limitation (i.e., from accidents or injuries) and potentially with changes in dietary and physical activity patterns. The individual-level fixed effects would not control for such changes over time.

Additional strengths of my study are that unlike previous studies that use self-reported data, this study used weight measured as part of healthcare visits, which is more reliable than self-reported data (Nawaz et al., 2001). Also, I used a novel mobility limitation variable that could identify a large group of individuals with mobility limitations. Research using such a large sample was made possible by leveraging healthcare administrative data and employing a predictive mobility limitation algorithm that had strong sensitivity and specificity. Examining the broad group of people with mobility limitations (vs. specific health conditions associated with mobility limitation) helps provide evidence that is relevant to a broader population of veterans who share common characteristics and challenges related to mobility. Finally, I empirically explored relationships that are described in the WHO's ICF (World Health Organization, 2001) but that have not been empirically studied with such large cohorts. Using the ICF as a conceptual framework, I focused on the interactions of mobility limitations with age, comorbidities, and baseline BMI category in affecting BMI. The stratified analysis showed how the relationship between mobility limitation and BMI varied for different subgroups. Future research could link WAVES data or other similar datasets to data on social participation to enhance the analysis completed here and to understand if and how social participation may also alter the relationship between mobility limitation and BMI, or how mobility limitation and BMI affect social participation as an outcome.

2. **Robustness of the findings**

Through several sensitivity analyses, I show the robustness of these findings. I modified the cut-off used in the algorithm and found similar findings in the same direction and magnitude. There were similar results when I added a variable for spinal cord injury, excluded those with quadriplegia and paraplegia, and when I modified the Quan comorbidity index. The alternative approach to test if I would have defined mobility limitation based simply on those with wheelchairs suggested that receiving a wheelchair was actually associated with a decrease in BMI.

Because the mobility limitation algorithm was highly sensitive, it may be over-classifying people with mobility limitations (more false positives). Results from the alternative categorical version of mobility limitation address the possibility that false positives (not true positives) were driving the results in the binary version of mobility limitation. The results of models with the categorical version showed a similar pattern as with the original binary mobility limitation variable. In pooled cross-sectional models, those with a high likelihood of having a mobility limitation had a strong association with BMI, but then in fixed-effects models, the effect was reduced and was lower than either the possible mobility limitation group or the original binary mobility limitation variable. Separating out the high likelihood of a mobility limitation group from the possible mobility limitation group reinforced that the effect of mobility limitation on BMI is very small. The fact that the association with BMI was highest for the high likelihood of mobility limitation group in pooled cross-sectional models suggests that within this group there is more unobserved heterogeneity than in the possible mobility limitation group. Given the problem of reverse-causality, the high-likelihood of mobility limitation group is also more obese. Once time-invariant unobserved variables are accounted for in the fixed-effects models, the effect of having a high likelihood of mobility limitation on BMI is relatively small at only 0.018 BMI unit increase for males.

My results showing the small effect of mobility limitation on BMI are similar to those from a study by Holmgren, Lindgren, de Munter, Rasmussen, and Ahlstrom (2014), who found no significant difference in change in BMI among people with mobility limitations and those without over an eight year period. Their study had a considerably smaller sample, and did not adjust for any confounding variables. The magnitude of the reported mean difference was in a similar range to my study at 0.078 BMI units. Findings from both studies suggest that developing a mobility limitations leads to increases in BMI, but the magnitude of the increase is small.

3. **Mobility limitation impact on BMI across age groups**

My findings also suggest that the effect of a mobility limitation on BMI changes across the life course. Veterans ages 20-39 who acquire a mobility limitation had the biggest increases in BMI compared to other age groups. However, the magnitude of the effect was still small at 0.09 BMI units ($p<0.001$) for males and 0.10 BMI units ($p<0.001$) for females. The effect of mobility limitation on BMI lessened with age and was associated with a decrease in BMI in male veterans older than 65. The decrease in BMI associated with a mobility limitation for older male veterans with a mobility limitation may be related to frailty (e.g., functional decline overall) (St-Arnaud-McKenzie et al., 2010). de Munter et al. (2016) examined the effect of mobility limitation on BMI across young, middle age, and older adults in a population-based study in Sweden and found a decreasing effect of mobility limitation on BMI as age increased. When compared to my study, the magnitudes of the effects were larger in de Munter's study. For instance, de Munter et al. estimated an effect of an acquired mobility limitation of 1.41 BMI units in females 18 to 39-year-old, whereas I calculated an effect of 0.104 BMI units among female veterans ages 20-39. However, it should be noted that their study assessed changes that took place over an eight year period and could reflect a compounding effect of mobility disability on BMI over time. We did not have a long enough panel to assess comparable longer-run effects.

4. **The role of comorbidities**

Developing a mobility limitation and having no comorbidities, some comorbidities, or many comorbidities at baseline were all associated with an increase in BMI. The effect was largest for veterans with many comorbidities at baseline. Those with many comorbidities are likely to have more healthcare utilization, hospital stays, and possibly nursing home stays due to the severe nature of the conditions that make up the comorbidity index. One explanation for the larger increase in BMI among those with many comorbidities is that those with mobility limitations are receiving additional treatment or rehabilitation related to their mobility limitation, which are affecting either diet or sedentary behavior or both. Forman-Hoffman et al. (2008) showed that the onset of several medical conditions was associated with greater than 5% weight gain. However, they did not examine the effect of mobility limitation at different levels of comorbidity or combine health conditions into an index. Those with many comorbidities might be on more medications, some of which may be associated with increased weight gain (Vanina et al., 2002). Finally, it is also possible that there are differences in the severity of mobility limitation between those with none, some, and many comorbidities, which may lead to a differential effect of mobility limitation on BMI. Further research that can distinguish between mild, moderate, and severe mobility limitation is needed to explore that possibility.

5. **Similarities and differences in impact by baseline BMI category**

Results from this study show that veterans who are obese at baseline have a greater increase in BMI compared to those who are not obese at baseline. These findings align with previous studies that examined changes in BMI over time by baseline category of BMI. Stenholm et al. (2015) studied weight gain in middle age and older adults in the general population and found that those starting in class-1 and class-3 obese categories did not gain as much weight as those in normal and overweight categories. A study of change in BMI among people with SCI also found that being underweight or of normal weight prior to injury led to a increase in BMI (0.05 BMI units), and being overweight and obese led to decreases in BMI (-1.4 BMI units) (Powell et al., 2017). There was a similar result in our analysis of mobility limitation being associated with increasing BMI for those who were underweight and normal weight, but I did not find a decrease in BMI for those who were obese or overweight in this study. For those who were obese, mobility limitation was associated with an increase in BMI, but this was smaller than normal weight and underweight for males. Thus, being obese and having a mobility limitation does not substantially raise the risk of increases in BMI compared to other weight categories. With that said, these findings suggest that for people in all BMI categories, weight management interventions may have positive benefits of preventing weight gain. For those who are obese and have a mobility limitation, reductions in BMI may help in preventing chronic diseases and further disability that are known to accompany obesity (Liou et al., 2005). The magnitude of increase in BMI for those who are of normal weight and overweight was not clinically significant in this study, but may accumulate over time, especially among those who are younger in age. People who are underweight may be receiving interventions to increase weight, which may be a reason for that group having the largest increases. However, further investigation is needed to understand the increase in BMI for those who are underweight. The lack of variation in the effect of mobility limitation on BMI across baseline BMI categories may have to do with our sample being older, and therefore less likely to be gaining weight no matter what their baseline BMI category.

6. **Implications for public health policy**

These findings inform health policy and obesity prevention by identifying the degree to which mobility limitation is associated with increases in BMI, and by teasing out some subgroups who have stronger associations with increases in BMI as a result of a mobility limitation. Although my findings suggest that people with mobility limitations do not gain substantially more weight than those without a mobility limitation, when taken another way, they also imply that people with mobility limitations are at roughly the same level of need for obesity prevention efforts. However, an abundance of literature has described how people with mobility limitations experience significant barriers to accessing health promotion opportunities, including lack of transportation (Jaarsma, Dijkstra, Geertzen, & Dekker, 2014), inaccessible facilities (Vasudevan, 2016), neighborhood built environment barriers (Rosenberg, Huang, Simonovich, & Belza, 2013), and discrimination (Rimmer, 2005). Weight management best practices, such as being regularly weighed, are less likely for this population (Locatelli & LaVela, 2016) and this population is less likely to be recommended physical activity by their physicians (C. Carroll et al., 2014). Because younger adults had the largest increases in BMI associated with mobility limitation compared to older groups in this study, weight management initiatives may want to target their efforts on people with mobility limitations less than 40 years of age.

F. **Limitations**

This study had limitations. The mobility limitation algorithm was limited in that it was developed from a relatively small sample (n=964) of only Medicare beneficiaries, and has not been validated beyond that sample. Nonetheless, the frequencies found in this study for those with mobility limitations total and those certain health conditions and mobility limitations are similar to other studies and datasets, which provide some face validity to the algorithm.

Another limitation to generalizability is that veterans in this study are only those who utilize the VHA. In 2014, an estimated only 42% of all veterans were enrolled in the VA healthcare, and between 63% - 65% of those enrolled actually used VA healthcare (Bagalman, 2014). VHA users may be more likely to be lower income, unemployed, older, and have lower health status (Liu et al., 2005; Nelson et al., 2007). Also, veterans may be different in their healthcare utilization and since this study was based on healthcare administrative data, use of similar data for non-veterans may show different results. Although given the extensive sensitivity analyses, and what might be considered over-sampling of those with mobility limitations due to the use of VHA for assistive devices, it can be argued that findings in other settings are not likely to be substantially different.

Because the VA has a more generous benefits policy for assistive devices, veterans may be more likely to receive such a device in relation to having a mobility limitation (Hubbard Winkler et al., 2006). The assistive mobility device itself supports mobility in the community, and so veterans with mobility limitation may be more mobile than non-veterans with mobility limitation who may have more barriers to insurers paying for their assistive mobility devices. Medicare only pays for assistive devices to be used inside the home (Hubbard Winkler et al., 2006). Future research could compare provision of assistive devices between veterans and non-veterans to better understand the role of an assistive device as a moderator of the relationship between mobility limitation and weight gain.

BMI has shown to underestimate obesity prevalence among people with certain health conditions associated with mobility limitation, such as spinal cord injury and MS related to differences in how muscle mass deteriorates over time (Jones, Legge, & Goulding, 2003). The sensitivity analysis showed that there was no difference in the effect of mobility limitation on BMI, even when accounting for those with quadriplegia and paraplegia. However, additional research is warranted using other measures of fat distribution, such as dual-energy x-ray absorptiometry (Jones et al., 2003).

G. <u>Conclusion</u>

Findings from this study suggest that the effect of mobility limitation on BMI is not substantial. This does not imply that obesity is not a concern for people with mobility limitations, but that the mobility limitation itself is not the cause of the high rates of obesity seen among people with mobility limitations. This is the first study to estimate the effect of mobility limitation on BMI and to address many of the threats to causal interpretation. The mobility limitation algorithm in this study can be used in other studies to compare findings. The algorithm allowed for a broad group of people with various types of health conditions to be classified as having a mobility limitation or not. Because the effect of mobility limitation varies by age and comorbidities, these are important factors to consider in developing more targeted interventions for people with mobility limitations. Additional research is needed using a similar approach, but in a non-veteran sample.

III. DOES THE NEIGHBORHOOD ENVIRONMENT MODERATE THE EFFECT OF MOBILITY LIMITATION ON BMI?

A. Introduction

Research on neighborhood walkability and obesity suggests that the walkability of neighborhoods may be an important contextual factor that is associated with BMI (Chandrabose et al., 2019; Grasser, Van Dyck, Titze, & Stronegger, 2013; Mackenbach et al., 2014; Sallis et al., 2012). A walkable neighborhood is characterized as one that supports walking through connected street infrastructure, numerous types of destinations to walk to, and a dense population area where there are more people walking (Ewing & Hamidi, 2014; Frank et al., 2010). One important subgroup that could strongly benefit from research on walkability and obesity is individuals with mobility limitations. An estimated 31.5 million US adults have a mobility limitation, comprising the largest category of people living with a disability (Courtney-Long et al., 2015). People with mobility limitations are a particularly relevant group through which to examine the effect of neighborhood walkability on BMI. This is because 1) being less mobile means travel outside the home is more limited (Deka, 2014), making the proximal environment potentially more influential than for people without mobility limitation, 2) people with mobility limitations have higher rates of obesity (An et al., 2015; Rasch et al., 2008; Reichard et al., 2011), and 3) neighborhood walkability is often cited as a barrier to physical activity among people with mobility limitations (Rimmer, Riley, Wang, Rauworth, & Jurkowski, 2004; Rosenberg et al., 2013; Vasudevan, 2016). Despite the importance of the neighborhood environment for people with mobility limitations, no quantitative studies have empirically examined the effect of the neighborhood environment on obesity among people with mobility limitations.

Although mobility limitation is more common in older adults, studies on the relationship between walkability and BMI among older adults have infrequently included measures related to mobility limitation (Berke, Koepsell, Moudon, Hoskins, & Larson, 2007; Hirsch, Diez Roux, Moore, Evenson, & Rodriguez, 2014). The few studies that measured mobility limitation in their sample did not stratify their analysis to look at the relationship of walkability and BMI for those with mobility limitation (King et al., 2011; Michael, Nagel, Gold, & Hillier, 2014). Furthermore, conceptual models of disability and health suggest that the effect of mobility limitation on BMI may vary by contextual factors, such as the walkability of the neighborhood environment (World Health Organization, 2001). No existing studies were found in the published literature that focus on the interaction between the neighborhood environment and mobility limitation in modifying the effect of mobility limitation on obesity. In addition, none of the studies looked across the lifespan at older adults as well as those younger in age with mobility limitations. Studies on the effect of walkability on BMI are often limited in their ability to draw causal interpretations because they are cross-sectional, and do not account for unobserved heterogeneity or neighborhood self-selection (McCormack & Shiell, 2011). Such studies also tend to have smaller samples and are conducted in one geographic setting (Berke et al., 2007; Hoehner, Handy, Yan, Blair, & Berrigan, 2011).

To my knowledge, this present study is the first to examine the role of the neighborhood environment in moderating the relationship between mobility limitation and BMI. In this study, I utilize a rich dataset developed for an NIH R01 study (R01CA172726, VA IIR 13-085) that includes healthcare administrative data on 3.2 million veterans throughout the United States and a comprehensive set of neighborhood environment variables related to food access, physical activity opportunities, and walkability (Zenk et al., 2018). The analysis also benefits from a longitudinal panel study design with individual fixed effects, which help to address threats to the validity of causal interpretations by controlling for all time-invariant unobserved variables. The sample is not limited to older adults, but includes adults across the age spectrum. This is especially important for veterans, who can experience mobility limitations earlier in life due to their role in the military. Finally, I utilize a novel approach to identify individuals with mobility limitation in healthcare administrative data that facilitates ‘big data’ research without requiring additional efforts to survey veterans or conduct extensive physical tests on limitations in mobility functioning. ‘Big data’ research on people with mobility limitations is only possible with an extensive set of potential predictors that can account for health conditions, assistive devices, personal characteristics, and environmental factors—all of which contribute to and reflect aspects of a mobility limitation, but are not sufficient to identify mobility limitation on their own (Iezzoni, 2002). Large sample sizes are needed because they allow researchers to stratify their analyses or include interaction terms. Thus, important hypotheses can be tested concerning individuals with mobility limitation within the context of different ages, multiple comorbidities, or—regarding the focus of this chapter—differing neighborhood environments.

B. Background

1. Obesity among people with mobility limitations

The rate of obesity among adults in the United States has continued to increase over the last decade (Flegal, Kruszon-Moran, Carroll, Fryar, & Ogden, 2016). Nearly 40% of adults were obese in 2016, up from 34% of adults who were obese in 2008 (Hales, Fryar, Carroll, Freedman, & Ogden, 2018). Addressing the high rates of obesity is a public health priority because obesity is associated with greater levels of chronic diseases (Kopelman, 2007; Must et al., 1999), increased risk of disability (Peeters et al., 2004), and mortality (Flegal et al., 2007; Hruby et al., 2016).

Obesity is a major public health concern for people with mobility limitations (Fox et al., 2013; Froehlich-Grobe & Lollar, 2011). Studies examining the prevalence of obesity consistently report a higher percentage of obesity among people with mobility limitations compared to those without mobility limitations (An et al., 2015; Rasch et al., 2008; Reichard et al., 2011). An estimated 31.5 million US adults have a mobility limitation, comprising the largest category of people living with a disability (Courtney-Long et al., 2015). Mobility limitations include difficulty with several physical tasks, including walking, climbing stairs, and transferring in various environments (Patla & Shumway-Cook, 1999). When mobility limitation becomes severe and restricts an individual’s ability to move around in their environment, mobility becomes a disability. This functional limitation is particularly prevalent among older adults, but also affects significant numbers of middle-aged people (Gardener, Huppert, Guralnik, & Melzer, 2006; Iezzoni et al., 2001). New approaches addressing the high rates of obesity among people with mobility limitations are needed (Fox et al., 2013; Froehlich-Grobe & Lollar, 2011).

2. **Environmental strategies to address obesity**

The Centers for Disease Control and Prevention (CDC) and other federal agencies promote environmental strategies as one way to combat the high levels of obesity in the US (Frieden, 2010). Environmental approaches focus on changing the physical activity and food environments to promote and sustain changes in health behaviors that prevent obesity (Sallis et al., 2006). For instance, the CDC Community Preventive Services Task Force recently recommended a strategy to improve walkability, which they define as combining interventions for the pedestrian environment with interventions for having more destinations in closer proximity to where people live, work, and play (The Community Preventive Services Task Force, 2016a). To become a recommendation, the Task Force assessed and found sufficient evidence in the literature of the effect of walkability on various types of physical activity (The Community Preventive Services Task Force, 2016b). The recommendation is used by local health departments and other local health organizations to develop policy and environmental interventions to improve walkability.

Research on whether neighborhood walkability affects BMI is not as consistent and requires further evidence. A study on a large nationwide sample of veterans and walkability using the same data that are utilized in this chapter (WAVES) indicated a significant effect of walkability on BMI, but with a relatively small magnitude (Tarlov et al., 2019). Several systematic reviews have reported mixed results for the association between walkability and BMI (Grasser et al., 2013; Mackenbach et al., 2014). However, a recent meta-analysis focusing on only longitudinal studies that examined the effect of walkability on obesity found that there was strong evidence (weighted z-value = 2.925, p=0.003) for a relationship between walkability and lower obesity (Chandrabose et al., 2019). The authors of that study argued that although different, their findings were stronger because they did not include cross-sectional studies and accounted for the quality of the methods in the studies they reviewed (Chandrabose et al., 2019). Several of these systematic reviews excluded studies of specific target populations, and so results may differ for certain subgroups.

3. **Neighborhood walkability and mobility limitation**

People with mobility limitations are an important subgroup that has not been studied in the literature on neighborhood walkability and BMI. Neighborhood environments are discussed as contributors to higher levels of physical inactivity seen in people with mobility limitations (C. Carroll et al., 2014) and subsequently higher rates of obesity (Fox et al., 2013; Liou et al., 2005). Because the activity space of people with mobility limitations is smaller (Casas, 2007; Vale, Ascensão, Raposo, & Figueiredo, 2017), there is likely a stronger influence of the proximal environment on neighborhood walking. People with mobility limitations are more likely to spend time at home (Mattson, 2012) and to use public transportation (Deka, 2014; Rosenbloom, 2007), which usually entails traveling shorter distances than for those who drive because of a higher level of mobility demands (Deka, 2014; Shumway-Cook et al., 2002). Finally, people with mobility limitations are an important group for neighborhood walkability research because several studies have described the poor conditions of the pedestrian network in cities: such conditions can deter individuals with mobility limitations from walking for leisure or as part of a commute (Kirchner, Gerber, & Smith, 2008; Rosenberg et al., 2013). Barriers in the neighborhood environment have also been described as determinants of engaging in physical activity in general (Rimmer et al., 2004; Vasudevan, 2016) Areas with higher walkability are more likely to have fewer barriers for people with mobility limitations because areas with more people walking are often priority areas for sidewalk redevelopment and maintenance (Federal Highway Administration, 2007). All areas with improvements to sidewalks since 1990 are more likely to be accessible to people with mobility limitations as this was a requirement under the Americans with Disabilities Act (ADA) (Americans with Disabilities Act of 1990, 1990) and especially after 2010, when new guidelines for construction of curb ramps and sidewalks were passed (United States, 2010). If neighborhood barriers deter both walking and physical activity among people with mobility limitations, it is important to understand whether living in areas with higher walkability can improve physical activity and reduce obesity. A few studies have examined the effect of neighborhood walkability on physical activity among people with mobility limitations, but these studies have produced mixed results (Eisenberg, Vanderbom, & Vasudevan, 2017).

4. **Lack of walkability studies on people with mobility limitations**

To my knowledge, there is no existing research on how neighborhood walkability impacts obesity for people with mobility limitations. Two studies on the effect of walkability on obesity among older adults have included a measure of mobility limitation as a covariate. King et al. (2011) included mobility limitation as a covariate in a cross-sectional study of neighborhood walkability and its association with BMI among older adults. Michael et al. (2014) looked at change in walkability and its impact on change in BMI among older women over an 18-year period, also including mobility limitation as a covariate. Unfortunately, the approach used in these two studies to model mobility limitation as a covariate did not address the question of how differences in neighborhood walkability differentially impacts BMI for people with mobility limitations. In other words, they did not examine how the effect of mobility limitation on BMI varies by different levels of neighborhood walkability. To do so requires the addition of an interaction term between variables on mobility limitation and the neighborhood environment.

5. **Previous research using walkability and mobility limitation interactions**

While the effect of the interaction between neighborhood walkability and mobility limitation on obesity has not yet been examined, there have been some informative results from a few studies that were designed to examine whether the level of physical activity among adults with mobility limitation depended on the walkability of their neighborhood. In three studies, two from the U.S. and one from Belgium, the authors found a significant interaction effect between neighborhood walkability and mobility limitation on physical activity (King et al., 2011; Satariano et al., 2010; Van Holle et al., 2016). Physical activity levels were higher in areas with higher neighborhood walkability, but only for those with less severe mobility limitations. For those with more severe mobility limitation, levels of physical activity did not differ between areas with low or high neighborhood walkability. Based on these results, we might assume that there would also be no difference in the effect of mobility limitation on BMI at different levels of neighborhood walkability.

One of the limitations of these studies examining the walkability X mobility limitation interaction is that they were all cross-sectional and did not address endogeneity bias. Not addressing endogeneity can bias results and limit causal interpretations about whether mobility limitation's effect on BMI differs by degree of walkability. For instance, (Zenk et al., 2017) show how cross-sectional analysis greatly overestimates the impact of the neighborhood environment on BMI. In the context of neighborhood environment research, the greatest endogeneity concern is residential self-selection, where people who engage in health promoting activities move to higher walkability neighborhoods where they continue these behaviors (Handy, Cao, & Mokhtarian, 2006; Mayne, Auchincloss, & Michael, 2015; McCormack & Shiell, 2011). In regards to mobility limitation, people with higher physical functioning may move to higher walkability neighborhoods more than those with lower physical functioning. None of the previous studies focusing on mobility limitation X walkability interactions addressed residential self-selection. Therefore, it is important to examine interaction effects using an approach that accounts for unobserved heterogeneity and residential self-selection.

6. **Neighborhood poverty as a moderator of walkability effects**

The effects of neighborhood walkability on BMI have also been shown to vary by neighborhood socio-economic status (SES), with low SES being an important factor even in high-walkability areas (Lovasi, Neckerman, Quinn, Weiss, & Rundle, 2009; Rundle et al., 2008). Neighborhood SES may reflect aspects of the physical and social neighborhood environment that affect walking activity. For instance, areas that have a high rate of poverty are negatively associated with neighborhood attractiveness (Handy et al., 2006; Saelens & Handy, 2008) and positively associated with crime (Hsieh & Pugh, 1993), both of which can affect walking activity. Because of these factors, a high-walkability neighborhood that is also impoverished may not be perceived as highly walkable. It is important to understand if the effect of mobility limitation on BMI changes with different combinations of walkability and neighborhood SES. Van Holle et al. (2016) found that being in a high-income, high-walkability neighborhood was associated with higher physical activity for people with mobility limitations, but that there was no difference in physical activity in low income neighborhoods whether they were low or high-walkability. No studies have examined the differential impact of the combinations of low-high SES and low-high walkability on BMI among people with mobility limitations.

7. **Contribution**

This study adds to the current research on neighborhood walkability and BMI by exploring the role of neighborhood walkability in moderating the relationship between mobility limitation and BMI. To my knowledge, this is the first study to test whether having a mobility limitation and living in a high-walkability neighborhood serves as a protective factor that modifies the effect of mobility limitation increasing BMI, or at the same time, whether living in a low-walkability neighborhood further increases the effect of mobility limitation on BMI. I overcome some of the limitations of previous cross-sectional studies on the interaction between neighborhood environment and mobility limitation by addressing unobserved heterogeneity through the use of longitudinal individual and year fixed-effects models.

I leveraged a large data source developed for an NIH R01 study called the Weight and Veterans Environments Study (WAVES). This dataset provided the opportunity to study a large population of the same individuals over time. The fixed-effects approach controlled for all unobserved time-invariant predictors, which in cross sectional models can be correlated with the error term and bias results (Wooldridge, 2015). Wooldridge (2015) explained that the error term in a panel dataset is made of two error components: a_i and u_{it}. a_i is the time-invariant error and u_{it} is the time-varying error or idiosyncratic error. a_i is also called the fixed effect, meaning that it is 'fixed' over time. By including a_i (the fixed effect), we controlled for all time-invariant unobserved factors that might be correlated with mobility limitation and BMI. So factors such as gender, race, general education level, genetic predispositions, family history of obesity etc. are controlled for through inclusion of the fixed effect. Although the ability to control for all time-invariant unobserved/unmeasured factors strengthens causal inference, the strict exogeneity assumption still applies (Wooldridge, 2015), which in this case would be the assumption that the idiosyncratic error u_{it} is not correlated with mobility limitation or walkability. In other words, the assumption is that there are no time-varying omitted variables that are correlated with the error term.

The study design used in this chapter addresses some important threats to internal validity by inclusion of key time-varying factors about 1) changes in individual health, such as increase in chronic health conditions, 2) changes in the neighborhood environment, such as fast-food restaurants, and 3) residential movement. Additionally, the analysis is strengthened by including objectively measured weight data and other variables derived from healthcare administrative data, objective geographic information systems (GIS) based measures of the neighborhood environment, and a large diversity of geographic areas that cover the continental US.

8. Purpose

The purpose of this chapter is to explore whether the effect of a mobility limitation on BMI is reduced in high-walkability neighborhoods when compared to low-walkability neighborhoods. My research questions are:

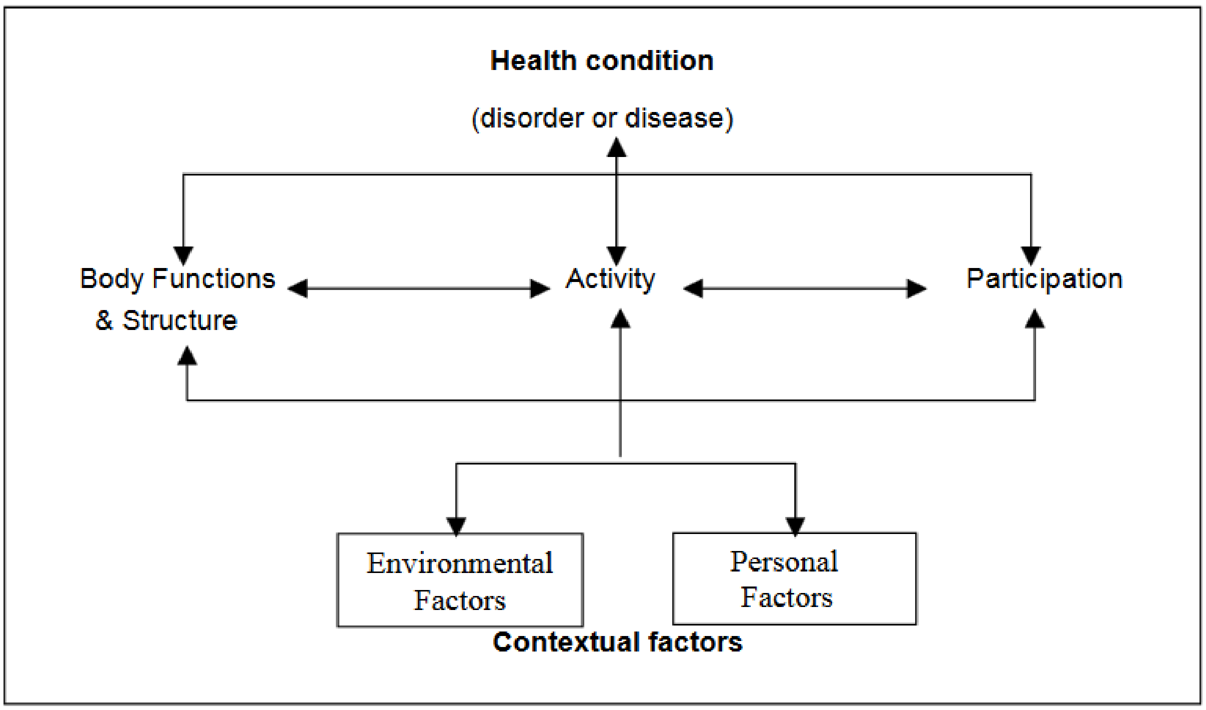
1) Is the effect of a mobility limitation on BMI reduced in a high-walkability neighborhoods when compared to low-walkability neighborhoods?
2) How does the interaction between mobility limitation and neighborhood walkability affect BMI across the life course?
3) How does the interaction between mobility limitation and neighborhood walkability affect BMI in low, medium, and high-poverty neighborhoods?

C. Methods

1. Conceptual model

The WHO's International Classification of Function, Disability and Health (ICF) provides a useful framework for studying mobility limitation and BMI at different levels of neighborhood walkability (see figure 7). The ICF is a biopsychosocial model of disability that serves as a conceptual framework and an important tool for studying disability (World Health Organization, 2001). In the ICF, human functioning is expressed across three domains of body function/structure, activities, and participation. Individuals can experience limitations in any of these domains. Functioning is moderated by environmental, personal factors, and health conditions. Mobility is a subdomain within the activity domain. In the ICF, mobility disability is seen as an interaction between one's mobility limitation and contextual factors, personal factors, and health conditions. As an example, an individual with difficulty walking who uses a walker to ambulate will have less mobility disability in the context of a community that is universally designed for residents of all abilities, compared to a community that has significant physical environment barriers, such as a lack of sidewalks, broken curb ramps, and unsafe intersections (Kirchner et al., 2008; Rosenberg et al., 2013).

Figure 6: International Classification of Function, Disability and Health (ICF) (World Health Organization, 2001)



Based on the ICF, obesity (a health condition) can result from an interaction between mobility limitation, personal factors, such as age, and environmental factors (Robinson & Butler, 2011), which would include neighborhood walkability.

2. **Data sources**

The dataset used in this analysis is from WAVES, which developed a longitudinal cohort of veterans using data housed in the VHA Corporate Data Warehouse (CDW), such as electronic health records, durable medical equipment, and Medicare claims as well as data on the neighborhood environment that were developed for the continental US using public and private data sources (Zenk et al., 2018). Data from Medicare claims were not available for the years 2014 and 2015.

A previous paper on WAVES provided detailed information about how the geographic variables used in this chapter were developed, and how they were merged with person-level healthcare administrative data on veterans (Zenk et al., 2018). Briefly, objectively measured geographic variables were created using smart mapping techniques for each year of the study (2009-2014) for the continental US. Both one-mile and three-mile buffers around a veteran's home address were used to calculate counts and densities of food and physical activity destinations. Time-varying neighborhood environment data were developed for each year of the study with a focus on data from the end of the year. These data were then linked to BMI measurements in the following year so that changes to the environment could logically come before the BMI measurements. Data on the food environment were purchased through InfoUSA and Dun & Bradstreet, and data on the physical activity environment were derived from NAVTEQ, Teleatlas and InfoUSA. The data were developed for the years 2009 – 2014 (Zenk et al., 2018). The data on person-level and geographic variables were developed as an annual panel in the long form. Further details on variable construction are described below.

3. **Sample**

Because data from WAVES come from healthcare administrative data and are not collected on set time-interval, WAVES is an unbalanced panel dataset. Veterans have between 2-6 years in the study and there can be gaps. Gaps in the panel reflect years when a veteran did not visit the VA and have their weight measured. Thus, years with missing BMI do not contribute to the data in that year.

The inclusion criteria for WAVES was having at least one visit to a VA facility in the two years prior to their baseline year. The visit could be for inpatient or outpatient services. The sample included veterans ages 20-80 at their first visit in the study period.

A subset of the WAVES sample was used for this study and only includes veterans living in large central metropolitan counties defined by the National Center on Health Statistics (NCHS) as counties in Metropolitan Statistical Areas with a population above 250,000 (Ingram & Franco, 2013). Outside of large central metropolitan counties, the walkability measures have a different meaning, as only a small percentage of the county may be walkable and the rest is surrounded by county roads and highways where walking is very unlikely (Kegler et al., 2015). I included person-year observations for veterans whose residence was in a large central metropolitan county. There are 68 large central metropolitan counties in the US whose residents make up 30% of the US population (Ingram & Franco, 2013). Key to this chapter is that there is substantial variation in walkability within those counties.

Veterans who had no height measurement, who were without at least two weight measurements, who had no geocodable home address for any of the years, or who had a long nursing home stay at baseline (greater than 90 days) were excluded. There were 864,358 veterans and 3,841,820 person year observations for those who met these criteria lived in central metropolitan counties. Additionally I excluded the person-years of individuals who had an amputation for the year of the procedure and any year after. Amputations were defined by ICD9 procedure codes. Not excluding the years that an individual had an amputation and after could skew the data because of a potentially large decrease in weight as a result of the amputation. There were 10,496 veterans who had an amputation during the study. I excluded 33,417 person-year observations for the years during and after an amputation.

I also excluded records in years after an individual died. This may occur when some administrative records do not catch up to the death records. Death records are a set of administrative data from the VHA Vital Status Master File, which combines records from VHA hospitals, family members applying for death benefits, VA National Cemetery Administration, hospital inpatient stays, reports to the Social Security Administration, and the Medicare vital status file (Sohn et al., 2006; VA Information

Resource Center, 2018). I merged the data on deaths to the WAVES data using the unique combinations of study ID and year. There were 67,213 (8%) veterans who died at some point during the study period. There was only one record that needed to be removed because it was in the year after an individual died. The final sample had 842,861 veterans and 3,808,402 person-year observations.

4. Measures

a. Outcome

Weight and height were obtained from patient-level encounters (Zenk et al., 2018). An annual BMI measurement was calculated from measured height (the modal value across all years of data) and the mean of all outpatient weight measurements in the second half of each calendar year (if none, weights from the first half of the year were used) (Zenk et al., 2018). Years with no weight measurement had missing values (no imputation) for the outcome and thus did not contribute to the model estimation.

b. Independent variable of interest

Mobility limitation was a binary variable based on a model developed by Shumway-Cook and colleagues (Shumway-Cook et al., 2005). In chapter one, I developed a mobility limitation algorithm using data for a subset of veterans who had also participated in the Medicare Current Beneficiary Survey (MCBS) as a development dataset. That dataset included self-reported difficulty walking and difficulty walking a quarter mile. To predict a veteran’s self-reported mobility limitation (modeled as dichotomous), I used healthcare administrative data concerning assistive mobility device use, health conditions related to mobility limitations, demographics, and healthcare utilization. The predictive model had a high Area Under the Curve (AUC) (0.80), which means that the model did well at distinguishing between those with and without a mobility limitation. It also had a high sensitivity (70%), meaning that the algorithm correctly identified a large percentage of those with mobility limitations and a high specificity (79%), meaning that the algorithm also did well at ruling out people who did not have a mobility limitation. I made one modification to the algorithm by removing the BMI predictor because in this study, BMI is the outcome.

The equation and coefficients used in this analysis were:

(5): y*moblim* = -1.42constant + 3.15*homemod* + 2.06*copd* + 1.88*wheelchair* + 1.53*orthpros* + 1.15*cns* + 1.10*gait* + 0.84*division* + 0.82*depression* + 0.81*pvd* + 0.64*musculoskeletal* + 0.53*diabetes* + 0.38*prioritygroup*

Where y*moblim* is the predicted binary outcome (0-1) for having a mobility limitation, the constant is the intercept; *homemod* is home modifications, such as ramps and lifts; *copd* is Chronic Obstructive Pulmonary Disease; *wheelchair* is receipt of a manual or power wheelchair; *orthpros* receipt of orthotics or prosthetic devices for walking; *cns* is diseases of the central nervous system; *gait* is abnormalities of gait or diagnosis of difficulty walking; *division* is being in census division seven (West South Central); *depression* is diagnosed with clinical depression; *pvd* is peripheral vascular disease; *musculoskeletal* is having a diagnosis for a condition related to the musculoskeletal system or connective tissue; *diabetes* is having a diagnosis for diabetes mellitus with or without complications, and *priority group* is being in priority group 1, which is related to a service-connected disability or being 'home-bound'. The model was estimated using a logistic regression model. Predicted values for mobility limitation were then calculated based on estimation results (coefficients shown in equation (5)) for each year of the data for the full WAVES sample. Predicted values ranged from 0-1.

To create the binary variable indicating a veteran has a mobility limitation, it is necessary to establish a cut-off point whereby those above the cut-off are coded as having a mobility limitation and those below the cut-off are coded as having no mobility limitation. I chose to use a cut-off of 0.412, which was the point on the receiver operator curve that minimizes false positives and false negatives, also called Youden's index (Youden, 1950). This, in turn, maximizes sensitivity and specificity. If one of the variables in the mobility limitation algorithm was missing for a particular year, the mobility limitation variable was not calculated for that year. However, there were no missing values for the variables used in the algorithm.

Regressing BMI on mobility limitation in the same year suffers from the problem of reverse causality of obesity causing a mobility limitation. The estimated effect captured both the effect of mobility limitation on BMI and the effect of a high BMI that leads to a mobility limitation. To address this issue, I used a lagged mobility limitation variable that estimated the effect of having a mobility limitation in the previous year on BMI in the current year. The lag strengthens our argument that the change in BMI reflects the effect of mobility limitation. The disadvantage was that in using this approach, one year of data were lost. So only the subject's second year until their last year of data were used, for a maximum of five years.

c. Neighborhood walkability

A walkability index was constructed in previous analyses and captured the walkability of the area within a 1-mile buffer of the veteran's home (Tarlov et al., 2019). The index was built off a combination of variables that were identified in previous research as being associated with walkability: walking destinations, street connectivity, population density, and housing density (Ewing & Hamidi, 2014; Slater, Nicholson, Abu Zayd, & Chriqui, 2016). A proxy for walking destinations was used based on the number of jobs in the census tract within sectors that are considered walking destinations, such as retail, food, hospitality, entertainment, recreation, and arts (Huang, Moudon, Zhou, & Saelens, 2019). Data on employment for those walkable destinations were obtained at the census block level from the LEHD Origin-Destination Employment statistics (U.S. Census Bureau). Street connectivity was measured as the number of intersections in the 1-mile buffer and the percentage of 4-way intersections. Population and housing density were calculated based on the number of people or housing units per square mile from the American Community Survey (ACS) five-year block group level estimates. For each component of the index, z-scores were calculated and an average was taken across the 5-scores. A walkability index score was calculated for each year from 2009-2014. The measure was divided into quartiles. A similar variable was developed using a ¼ mile distance to use in a sensitivity analysis (Tarlov et al., 2019).

d. <u>Neighborhood environment covariates</u>

Other food and physical activity environmental characteristics beyond those identified as destinations in the walkability index might influence the relationship between mobility limitation and BMI; therefore I included additional time-varying neighborhood environment measures developed in WAVES, which measured the food and physical activity environments within one mile of veterans' homes.

Quartiles of the count of supermarkets, grocery stores, fast food restaurants, and convenience stores were included to reflect the food environment of the local neighborhood. Food environment data were obtained from InfoUSA and Dun & Bradstreet. I included two variables concerning the physical activity environment. They were quartiles of the counts (1) of parks and recreation areas, and (2) of public and commercial fitness facilities, which both came from NAVTEQ, TeleAtlas, and InfoUSA.

At the census tract level, I included a variable for the percent of residents below the federal poverty level and another for median household income as controls for neighborhood SES. Both measures were derived from the American Community Survey (ACS) five-year census tract level estimates.

e. <u>Person-level covariates</u>

I selected person-level covariates that I hypothesized could be correlated with both BMI and mobility limitation. I only used covariates that change over time because all time-invariant variables are omitted from any of the fixed-effects models. I used a gender variable to run separate models for men and women. Marital status (married, single, widowed etc.) was included because being married is correlated with higher BMI (Klos & Sobal, 2013; Sobal et al., 1992) and potentially to mobility limitation in cases where a veteran may have a partner who is also a caregiver (Pienta et al., 2000). Age category dummy variables were for ages 20 to 39, 40-49, 50-64, 65-74, and 75+. These related to young, middle age, older middle age, older age, and very old age respectively.

Several comorbidity indices exist for studying comorbidity in healthcare administrative data and which weight diseases based on severity and likelihood of mortality. The Charlson Comorbidity Index was developed in 1987 to predict risk of inpatient mortality and used a set of 17 chronic conditions

(Charlson et al., 1987). Quan et al updated the Charleson Comorbidity index in 2011 with new weights that better reflected progress made concerning the life expectancy of certain diseases (AIDS) (Quan et al., 2011). The Charleson and Quan indices are used regularly in health services research studies on utilization (Yurkovich et al., 2015) and outcomes, such as mobility limitation, (Wells et al.) as a way to control for subjects' co-occurring health conditions that are severe. In my study, it is important to control for comorbidities as they could be associated with BMI and mobility limitations. Related to severity of diseases, comorbidities can lead to weight loss as well as to mobility limitation (Forman-Hoffman et al., 2008). I calculated the comorbidity score based on weights developed by Quan et al. (2011). Similar to other studies, I collapsed the comorbidity score into three groups based on a score of 0, 1-3, and ≥ 4 representing none, some and many comorbidities (Johnston et al., 2015; Yang et al., 2015).

As part of a natural dying process, people generally lose weight in the months prior to death (Alley et al., 2010). Because dying could be correlated with BMI and mobility limitation, I controlled for dying using death records available as part of the WAVES data. I developed two dummy variables to account for these unobserved aspects of the dying process, one for if a veteran died in that year, and another if they died in the first six months of the subsequent year, including in the year after the study period (2015).

I included three covariates representing health conditions that could change over time, and which could be correlated with both mobility limitation and change in BMI. As with the other health conditions already described, these were also identified through ICD9 diagnosis codes. I used two mental health conditions, substance abuse disorder, and depression. Finally, I included stroke as a covariate because it is one of the leading causes of mobility limitation (Wesselhoff et al., 2018). Obesity is a risk factor for stroke, but a stroke can also impair swallowing function and lead to weight loss (Oesch et al., 2017).

I included four variables on healthcare utilization. Having more hospital admissions may reflect acute health problems or a worsening health status that could affect both BMI and mobility limitation. Additionally, length of stay is important to control for because longer stays in the hospital are associated with weight loss (de Luis et al., 2006; Kyle et al., 2005) and possible mobility limitation due to the severity of the health related event (Bodilsen et al., 2016). The number of primary care visits and the number of specialist visits were included because they may reflect an unobserved health problem affecting mobility limitation. These visits may also reflect treatment or rehabilitation that could affect both mobility limitation and BMI.

5. **Descriptive analysis**

I began by running descriptive statistics for all covariates using the subjects' second year in the study because the first year was dropped to develop the lagged mobility limitation variable. The second year was most often 2010, but was sometimes later for subjects who entered the study later. I examined whether proportions of the variables were different by mobility limitation status using Z-test of proportions. Continuous normally distributed variables were compared using ANOVA, and continuous non-normally distributed variables were compared using Wilcoxon rank-sum test.

6. **Linear regressions**

I ran ordinary least squares (OLS) regression models with individual fixed effects to control for all time-invariant omitted variables and year fixed effects to control for secular trends over time. In longitudinal data, there is serial correlation between error terms in different years among observations for the same individual, which is a problem because it violates the OLS assumption that error terms across observations are not correlated (Wooldridge, 2015). To control for this problem, I clustered the standard errors on the individual to obtain robust standard errors in all the fixed-effects models. In addition, because the mobility limitation variable is a predicted variable and includes some measurement error, I bootstrapped the standard errors for the mobility limitation variable using 500 repetitions (Davison & Hinkley, 1997; Guan, 2003). In the second model, I added the environmental variables as separate main effects. In the third model, I included an interaction term between the mobility limitation variable and the walkability quartile variable. The equation for the third model with an interaction is:

$$(6):\ BMI_{it} = \beta_0 + \beta_1 moblim_{it-1} + \beta_2 walkability_{it} + \beta_3 moblim_{it-1} * walkability_{it} + \beta_4 X_{it} + \delta_3 T_t + a_i + u_{it},\ t=1,2,..5$$

Here, i is the person and t is time periods. BMI_{it} is the person-year specific BMI; β_0 is the intercept; $\beta_1 moblim_{it-1}$ is the main effect, lagged mobility limitation predictor; $\beta_2 walkability_{it}$ is the main effect of each veteran's walkability and $\beta_3 moblim_{it-1} * walkability_{it}$ is the interaction of mobility limitation and walkability quartile. $\beta_4 X_{it}$ is a vector of covariates representing Quan group, age group, substance abuse disorder, depression, stroke, marital status, hospital admission, length of stay, primary care encounters, specialist care encounters, and dying or dead in that year. $\delta_3 T_t$ is the time trend that is controlled through year fixed effects; a_i is the individual 'fixed effect,' and u_{it} is the time-varying or idiosyncratic error. I apply equation (6) to all the stratified and sensitivity analysis. I calculated marginal effects for mobility limitation across the four levels of walkability to make interpretation of all models easier. With marginal effects, the effect of mobility limitation vs. no mobility limitation is calculated at each walkability quartile using the average values for all other covariates in the regression model (StataCorp, 2017).

7. **Stratified analysis**

I used a gender variable to run separate models for men and women. This is common practice in assessing body weight outcomes because there are different average trajectories of BMI for males and females (Jackson et al., 2002; Wang & Beydoun, 2007). Additionally, the sample in WAVES was mostly male and so if combined, the results would mostly reflect that of males. Given that this gender disproportionality is one of the key observed areas that the VA sample differs from the general population, running separate models is important to avoid generalizability to the full population. I conducted a series of stratified analyses to examine how the interaction of mobility limitation and walkability varied across residential movement, age, and census tract poverty. I estimated separate models for those who moved their residence at some point during the study period (movers) and those who never moved (stayers) in order to address the potential bias among those who moved due to a change in individual preferences. Based on previous analysis (chapter two of this dissertation), the effect of mobility limitation on BMI varies substantially by age. Therefore, I ran stratified regression models across the five age group categories based on veterans' age group at their baseline year of the study. Finally, I ran stratified regression models across three tertiles (low, medium, high) of the percentage of people in a census tract below the federal poverty level to understand how the interaction effect between mobility limitation and walkability on BMI may also vary by the poverty level of the neighborhood.

8. **Sensitivity analyses**

I conducted five sensitivity analyses to test alternative forms of the mobility limitation and walkability predictors as well as potential threats of confounding variables. First, I tested how sensitive the results were to changes in the method I used to classify veterans as having a mobility limitation or not. From the predictive model of mobility limitation, I generated predicted probabilities that range from 0-1 and which required a cut-off to be established to classify mobility limitation as a binary variable. Instead of using the cut-off value that corresponded to the maximization of sensitivity and specificity, I changed the cut-off point by a value that represented a 5% increase in specificity from the original mobility limitation algorithm. So those above the value of 0.445 were now coded as having a mobility limitation and those below that value were coded as not having a mobility limitation. Increasing the specificity means that there are fewer false positives and more false negatives. So, less of the total sample was characterized as having a mobility limitation.

Second, individuals with more severe mobility limitations, such as those with quadriplegia, are more likely to have inaccurate weight measurement due to lack of weight scales and inaccurate weight measuring procedures (Locatelli & LaVela, 2016). Therefore, I ran a model excluding those with paraplegia and quadriplegia. Third, to test the sensitivity of the walkability variable, I re-ran the model with mobility limitation interacted with walkability based on ¼ mile distance from a veteran's home instead of 1-mile. Because some of the destinations related to food and physical activity were represented as both nearby destinations in the walkability index and as a separate covariate, the fourth sensitivity analysis tested how results changed with a model that just included walkability and none of the food or physical activity environmental variables.

As was done in the case of Chapter 2 of this dissertation, in order to address the possibility for over-sensitivity of the mobility limitation algorithm, I also developed a categorical mobility limitation variable. As similarly described in Chapter2, I started with the original binary mobility limitation variable. I created a second binary variable with a considerably higher cut-off that was based on a specificity of 95% as identified through the analysis in chapter one. Those above 0.722 were coded as having a mobility limitation. This group is essentially those with a high likelihood of having a mobility limitation. I combined the original binary variable with the high specificity binary variable using the logic that those classified as not having a mobility limitation by the original variable were coded as (0), those classified as having a mobility limitation in the original binary variable only were coded as (1), and those classified as having a mobility limitation variable in both the original binary and high specificity binary variables were coded as (2). Figure 8 illustrates the distribution of predicted values from 0-1, the location of each cut-off, and who was coded as each category. Essentially, these three categories represent (0) high likelihood of not having a mobility limitation, (1) possible mobility limitation, and (2) high likelihood of having a mobility limitation.

D. Results

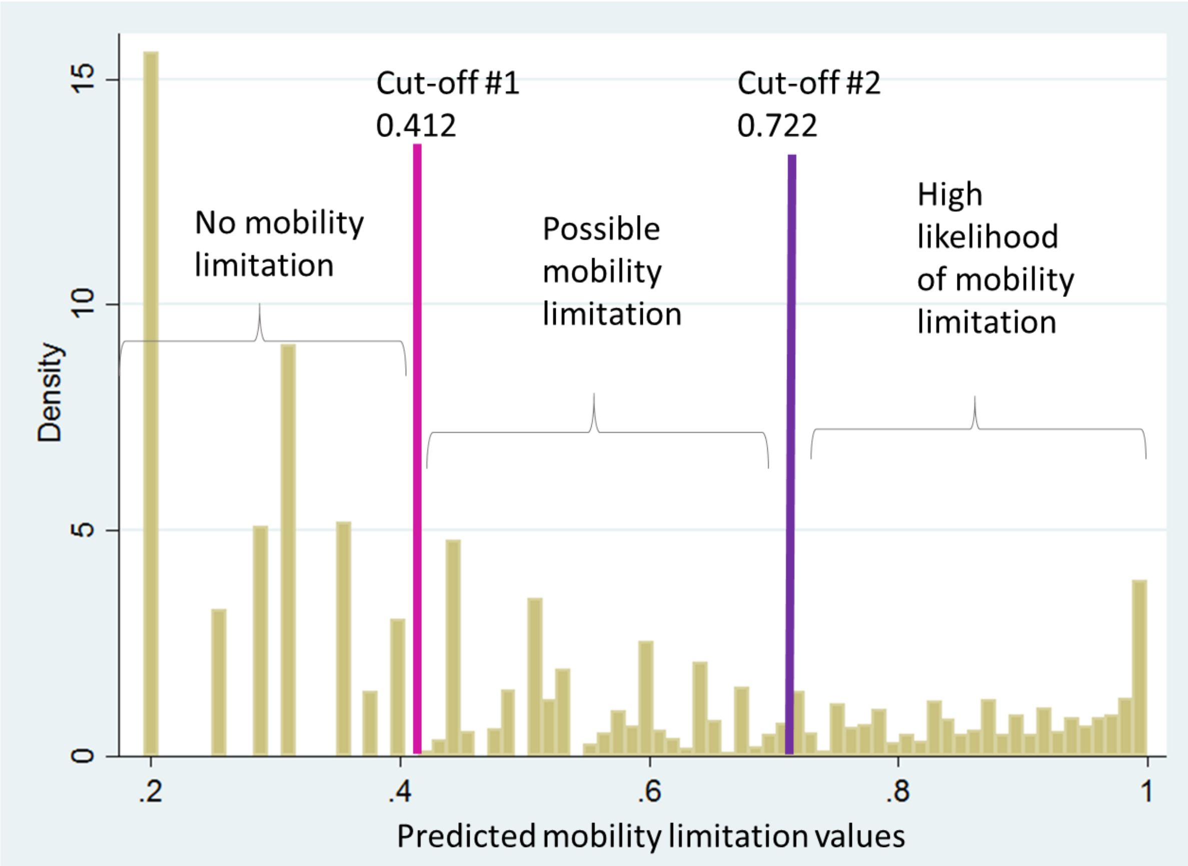
1. Descriptive statistics

In Table XVI, I summarize the characteristics of veterans who live in large central metropolitan areas in the United States for their second year in the study. The table is stratified by males and females and by those with and without mobility limitations.

The average BMI for males was 29.6 (SD 5.9) and most males were overweight (37.5%) or class-1 obese (25.9%), which was a BMI of 30-35. Males were mostly in the older age categories of greater than 50 years old (82%). Among males, 46.6% were married, 27.0% were separated or divorced, 21.4% were single, and 4.4% were widowed. The majority of males were white (52.3%) and 28.4% were black. Most males had no comorbidities (53.7%) on the Quan comorbidity index.

The average BMI for females was 29.6 (SD 6.5) and most females were overweight (30.4%) or class-1 obese (23.9%). A majority (54.1%) of females were under 50 years old and only 26.4% were married. A high percentage of females were white (42.2%) as well as black (7.5%). Most females had no comorbidities (74.4%) on the Quan comorbidity index.

Figure 7: Distribution of Predicted Mobility Limitation Values and Cut-offs Used for the Alternative Categorical Mobility Limitation Variable[a,b,c]



[a]The values in the histogram are the values that were predicted after a logistic regression was run for the sample in chapter one of this dissertation.

[b]Cut-off#1 is used for the original binary mobility limitation variable.

[c]Cut-off #2 is for the sensitivity analysis and represents a 95% specificity for the algorithm developed in chapter one of this dissertation.

A greater number of the male sample with a mobility limitation than those without are obese (46.2% vs 38.0%). The same is true for women (43.3% obese vs 38.4% obese). Compared to veterans without mobility limitations, a higher percentage of both males and females with mobility limitation are in older age groups, are separated/divorced, and widowed, have some (1-3) or many comorbidities (>4), are diagnosed with depression and substance abuse disorder, have had a stroke, and/or died during the study period. Hospital admissions, lengths of stay, and primary and specialists visits are all higher for both males and females with mobility limitations compared to those without.

In terms of the neighborhood environment variables, there were also some differences in frequencies of some of the variables. A higher percentage of veterans with mobility limitation lived in the lowest walkability quartile, and a lower percentage in the highest walkability quartile for both the 1-mile walkability measure and the quarter mile walkability measure. The difference was strongest for females as 58.3% of those with mobility limitations were in the bottom two quartiles, compared to 50.8% in those with no mobility limitation. More of the sample with mobility limitations lived in areas with zero parks, but more also lived in areas with 5+ parks. That similar pattern occurred for commercial fitness centers and supermarkets. There were not many differences in regards to the number of nearby convenience stores between those with and without mobility limitation. A higher percentage of females with mobility limitation compared to those without lived in the lowest quartile of grocery stores as well as the highest. More of the sample with mobility limitation than without lived in areas with 0-4 fast food restaurants, but a lower percentage lived in areas with 19+ fast food restaurants. In terms of poverty, fewer in the male sample with mobility limitation than without were in low poverty neighborhoods, and a higher percentage were in the highest quartile of neighborhood poverty. For females with mobility limitation, there was a similar proportion of females without mobility limitation in the lowest poverty quartile but a higher percentage in the highest poverty quartile. For median household income, it was the opposite; a higher percentage of both males and females with mobility limitations lived in the lowest income quartile and a lower percentage lived in the highest income quartile compared to those without.

2. **Regression results for the full sample**

In Table XVII, I summarized the results of the individual fixed-effects regression models. In the first model without environmental variables and only person-level covariates, the effect of a mobility limitation on BMI is 0.033 BMI units ($p<0.001$) for males and 0.096 BMI units ($p<0.001$) for females.

TABLE XVI: INDIVIDUAL AND NEIGHBORHOOD CHARACTERISTICS OF VETERANS IN LARGE CENTRAL METROPOLITAN AREAS AT BASELINE IN THE WEIGHT AND VETERANS ENVIRONMENTS STUDY 2009-2014

	Male				**Female**			
	ALL N=552,454	Mobility limitation[a] N=262,174	No mobility limitation N=290,280	p-value[b]	ALL N=46,576	Mobility limitation[a] N=23,741	No mobility limitation N= 22,835	p-value[b]
BMI (*M and SD*)	29.6 (5.9)	30.2 (6.3)	29.1 (5.5)	<0.001	29.6 (6.5)	30.5 (6.8)	28.9 (6.2)	<0.001
BMI category at baseline[c]								
Underweight	1.0	1.2	0.9	<0.001	1.3	1.2	1.3	<0.001
Normal weight	19.6	18.3	20.9	<0.001	24.5	20.8	28.2	0.664
Over weight	37.5	34.4	40.2	<0.001	30.9	29.6	32.3	<0.001
Class-1 obese	25.9	27.0	24.9	<0.001	23.9	25.0	22.8	<0.001
Class-2 obese	10.6	12.3	9.0	<0.001	12.4	14.4	10.3	<0.001
Class-3 obese	5.4	6.9	4.1	<0.001	7.1	9.0	5.1	<0.001
Age groups								
Ages 20 – 39	8.2	6.6	9.7	<0.001	31.4	25.6	37.5	<0.001
Ages 40 – 49	8.9	8.4	9.5	<0.001	22.7	23.1	22.4	0.044
Ages 50 – 64	43.1	45.0	41.4	<0.001	36.7	41.6	31.7	<0.001
Ages 65 – 74	24.9	24.7	25.1	0.001	6.4	6.8	5.9	<0.001
Age 74+	14.8	15.3	14.3	<0.001	2.8	3.0	2.6	0.004
Marital Status								
Unknown marital status	0.6	0.5	0.7	<0.001	0.9	0.7	1.1	<0.001
Married	46.6	47.8	45.5	<0.001	26.4	26.2	26.5	0.502
Separated/divorced	27.0	27.8	26.4	<0.001	34.2	36.8	31.4	<0.001
Widowed	4.4	4.8	4.0	<0.001	3.9	4.4	3.4	<0.001
Single	21.4	19.0	23.5	<0.001	34.7	31.9	37.7	<0.001
Race/ethnicity								
Non-Hispanic White	52.3	51.7	52.7	<0.001	42.2	43.6	40.8	<0.001
Non-Hispanic Black	28.9	30.5	27.4	<0.001	37.5	38.0	37.1	0.039
Hispanic	7.4	8.2	6.7	<0.001	8.0	7.7	8.3	0.016
Other – race	3.0	2.8	3.3	<0.001	3.8	3.5	4.2	0.001
Unknown race	8.4	6.8	9.9	<0.001	8.5	7.2	9.7	<0.001

TABLE XVI: INDIVIDUAL AND NEIGHBORHOOD CHARACTERISTICS OF VETERANS IN LARGE CENTRAL METROPOLITAN AREAS AT BASELINE IN THE WEIGHT AND VETERANS ENVIRONMENTS STUDY 2009-2014(CONTINUED)

	Male				**Female**			
	ALL N=552,454	Mobility limitation[a] N=262,174	No mobility limitation N=290,280	p-value[b]	ALL N=46,576	Mobility limitation[a] N=23,741	No mobility limitation N= 22,835	p-value[b]
Quan comorbidity score groups[d]								
Quan score: 0	53.7	39.4	66.6	<0.001	74.4	63.4	85.8	<0.001
Quan score: 1-3	37.8	47.7	28.8	<0.001	23.1	32.7	13.1	<0.001
Quan score: >=4	8.5	12.9	4.6	<0.001	2.5	3.9	1.0	<0.001
Quan comorbidity score (*Median (IQR*[e])	0 (0, 2)	1.0 (0.0, 2.0)	0.0 (0.0, 1.0)	<0.001	0 (0, 1)	0.0 (0.0, 1.0)	0.0 (0.0, 0.0)	<0.001
Health conditions, mortality and healthcare utilization								
Depression	23.7	43.4	6.0	<0.001	38.7	65	11.4	<0.001
Substance abuse disorder	17.3	22.2	12.9	<0.001	9.9	14.2	5.4	<0.001
Sarcopenia	0.3	0.5	0.0	<0.001	0.1	0.2	0.0	<0.001
Stroke	4.0	5.9	2.3	<0.001	1.5	2.2	0.7	<0.001
Died in the following year	1.1	1.6	0.7	<0.001	0.3	0.5	0.2	<0.001
Died in the same year	1.7	2.5	1.0	<0.001	0.5	0.7	0.2	<0.001
Number of hospital admissions (*Median (IQR*)	0 (0, 2)	0 (0, 0)	0 (0, 0)	<0.001	0 (0, 0)	0 (0, 0)	0 (0, 0)	<0.001
Length of hospital stays (*Median (IQR*)	0 (0, 0)	0 (0, 0)	0 (0, 0)	<0.001	0 (0, 0)	0 (0, 0)	0 (0, 0)	<0.001
Number of primary care encounters (*Median (IQR*)	0 (0, 0)	3 (2, 5)	2 (1, 3)	<0.001	3 (1, 4)	3 (2, 5)	2 (1, 3)	<0.001
Number of specialist encounters (*Median (IQR*)	2 (1, 4)	5 (2, 11)	2 (0, 5)	<0.001	4 (1, 9)	6 (2, 13)	2 (1, 5)	<0.001
Moved residential location[f]	3 (1, 8)	47.0	44.3	<0.001	56.4	56.8	55.9	0.066
Walkability Quartiles (1 mile)								
Quartile 1	25.0	25.7	24.4	<0.001	27.0	28.5	25.5	<0.001
Quartile 2	25.2	27.1	23.4	<0.001	27.6	29.8	25.3	<0.001
Quartile 3	24.9	23.8	25.8	<0.001	24.2	22.5	25.9	<0.001

TABLE XVI: INDIVIDUAL AND NEIGHBORHOOD CHARACTERISTICS OF VETERANS IN LARGE CENTRAL METROPOLITAN AREAS AT BASELINE IN THE WEIGHT AND VETERANS ENVIRONMENTS STUDY 2009-2014(CONTINUED)

	Male				Female			
	ALL N=552,454	Mobility limitation[a] N=262,174	No mobility limitation N=290,280	p-value[b]	ALL N=46,576	Mobility limitation[a] N=23,741	No mobility limitation N= 22,835	p-value[b]
Quartile 4	25.0	23.4	26.4	<0.001	21.2	19.2	23.3	<0.001
Walkability Quartiles (1/4 mile)								
Quartile 1	25.0	25.3	24.7	<0.001	27.0	27.8	26.2	<0.001
Quartile 2	25.0	25.3	24.7	<0.001	27.7	28.3	27.0	0.003
Quartile 3	24.3	24.4	24.1	0.01	23.8	23.9	23.6	0.52
Quartile 4	25.7	24.9	26.4	<0.001	21.6	20.1	23.1	<0.001
Parks (within 1 mile radius)								
0	29.6	30.5	28.8	<0.001	31.9	32.9	30.8	<0.001
1-2	25.6	25.5	25.7	0.195	24.1	23.5	24.8	0.001
3-4	31.2	29.4	32.8	<0.001	26.9	25.3	28.6	<0.001
5+	13.6	14.5	12.7	<0.001	17.1	18.3	15.8	<0.001
Commercial fitness facilities (within 1 mile radius)								
0	25.9	27.1	24.9	<0.001	26.7	27.7	25.6	<0.001
1-2	34.4	34.0	34.7	<0.001	34.4	34.2	34.6	0.336
3-6	26.6	24.7	28.2	<0.001	24.9	23.0	26.9	<0.001
7+	13.1	14.2	12.1	<0.001	14.0	15.1	12.9	<0.001
Supermarkets (within 1 mile radius)								
0	25.9	26.3	25.6	<0.001	26.6	26.8	26.4	0.286
1	19.0	18.6	19.4	<0.001	18.3	17.7	18.9	0.001
2	26.4	24.3	28.4	<0.001	24.4	21.9	27.0	<0.001
3+	28.6	30.8	26.6	<0.001	30.7	33.5	27.7	<0.001
Convenience stores (within 1 mile radius)								
0-1	26.1	25.2	26.9	<0.001	27.5	27.4	27.5	0.742
2-5	25.3	25.5	25.1	0.004	26.4	27.0	25.8	0.003
6-9	24.6	25.1	24.1	<0.001	24.5	24.7	24.4	0.534
10+	24.0	24.2	23.9	0.013	21.6	20.9	22.3	<0.001

TABLE XVI: INDIVIDUAL AND NEIGHBORHOOD CHARACTERISTICS OF VETERANS IN LARGE CENTRAL METROPOLITAN AREAS AT BASELINE IN THE WEIGHT AND VETERANS ENVIRONMENTS STUDY 2009-2014 (CONTINUED)

	Male				**Female**			
	ALL N=552,454	Mobility limitation[a] N=262,174	No mobility limitation N=290,280	p-value[b]	ALL N=46,576	Mobility limitation[a] N=23,741	No mobility limitation N= 22,835	p-value[b]
Grocery stores (within 1 mile radius)								
0	17.4	18.0	17	<0.001	18.1	19.3	16.8	<0.001
1	27.3	28.3	26.5	<0.001	27.6	27.3	27.9	0.195
2-5	24.6	23.3	25.8	<0.001	21.4	19.6	23.3	<0.001
6+	30.6	30.5	30.7	0.04	32.9	33.7	32	<0.001
Fast food restaurants (within 1 mile radius)								
0-4	28.0	29.6	26.5	<0.001	29.0	31.0	26.9	<0.001
5-10	27.3	27.7	26.9	<0.001	27.7	28.1	27.3	0.055
11-18	23.3	23.0	23.6	<0.001	23.3	22.8	23.8	0.011
19+	21.4	19.7	22.9	<0.001	20.1	18.1	22.1	<0.001
Percent below federal poverty level								
Quartile 1	23.8	22.2	25.2	<0.001	21.3	21.1	21.4	0.437
Quartile 2	24.3	23.4	25.1	<0.001	25.6	25.0	26.3	0.003
Quartile 3	23.2	23.8	22.6	<0.001	25.6	25.5	25.6	0.719
Quartile 4	28.7	30.6	27.0	<0.001	27.5	28.3	26.7	<0.001
Percent of the census tract below-poverty (*Median (IQR*)	12.9 (6.7, 23.5)	13.7 (7.1, 24.4)	12.2 (6.4, 22.6)	<0.001	13.2 (7.3, 22.8)	13.5 (7.4, 23.1)	12.9 (7.2, 22.4)	<0.001
Median household income								
Quartile 1	25.2	27.2	23.4	<0.001	23.1	24.2	22.0	<0.001
Quartile 2	25.3	25.6	25.1	<0.001	27.2	27.1	27.4	0.463
Quartile 3	25.0	24.6	25.3	<0.001	27.0	26.9	27.1	0.572
Quartile 4	24.5	22.6	26.3	<0.001	22.6	21.8	23.5	<0.001
Census tract median household income (*Median (IQR)*	48654 (35341, 65887)	47316 (34336, 64136)	49862 (36275, 67273)	<0.001	48727 (36337, 64242)	48235 (35786, 63523)	49234 (36922, 65018)	<0.001

TABLE XVI: INDIVIDUAL AND NEIGHBORHOOD CHARACTERISTICS OF VETERANS IN LARGE CENTRAL METROPOLITAN AREAS AT BASELINE IN THE WEIGHT AND VETERANS ENVIRONMENTS STUDY 2009-2014 (CONTINUED)

	Male				Female			
	ALL N=552,454	Mobility limitation[a] N=262,174	No mobility limitation N=290,280	p-value[b]	ALL N=46,576	Mobility limitation[a] N=23,741	No mobility limitation N= 22,835	p-value[b]

[a] Mobility limitation is a predicted binary variable derived from a model in chapter one.

[b] Using Z-test of proportions for all except for continuous variables that used Wilcoxon rank-sum test for non-normally distributed variables and ANOVA for normally distributed variables.

[c] Quan groups were generated from Quan comorbidity index (Quan et al., 2011).

[d] Defined by the CDC as underweight: <18.5, normal weight: 18.5-24.9, overweight 25.0 – 29.9, class-1 obese: 30 – 34.9, class-2 obese: 25 – 39.9 and class-3 obese: ≥40. (Centers for Disease Control and Prevention, 2017).

[e] IQR is interquartile range.

[f] Individual moved residence at some point between 2009-2014.

The magnitude of these effects represents a small increase of 0.22 pounds for a 5-foot 10-inch male and 0.56 pound increase for a 5-foot 5-inch female. In the second model, when the environmental variables are added, the effect of mobility limitation on BMI does not change. Additionally, for the main effect of walkability, increasing quantiles of walkability are associated with decreases in BMI compared to the lowest walkability quartile. For males, the effect of walkability was -0.001 BMI units ($p=0.924$) in walkability quartile two compared quartile one, and was -0.043 BMI units ($p<0.01$) in walkability quartile four compared to quartile one. For females, the effect of walkability was also -0.001 BMI units ($p=0.967$) in walkability quartile two compared to quartile one, and was -0.105 BMI units ($p<0.05$) in walkability quartile four compared to quartile one.

In the last model with an interaction term between walkability and mobility limitation, the effect of a mobility limitation changes by level of neighborhood walkability. The reference group in the model represents those with no mobility limitation in walkability quartile one. The effect of mobility limitation on BMI in walkability quartile one was 0.056 BMI units ($p<0.001$) for males and 0.151 BMI units ($p<0.001$) for females. For walkability quartiles two through four, the effect of mobility limitation on BMI relative to walkability quartile one lessens. For instance, in walkability quartile four, the effect of mobility limitation is 0.043 BMI units ($p<0.01$) less than the effect in walkability quartile one for males and 0.141 BMI units ($p<0.01$) less for females.

Additionally, with respect to covariates in the model with an interaction term, having some or many comorbidities was associated with a decrease in BMI relative to those with no comorbidities for both males and females. Higher age groups were associated with higher BMI for males and females, compared to those 20-39. An exception was females ages 75 and older, whose age group was associated with a decrease in BMI. The year fixed effects indicate that over time, males lost weight and females gained weight. Being widowed or single was associated with decreases in BMI for both males and females compared to those who were married. Having a diagnosis of depression was associated with an increase in BMI. Substance abuse disorder was associated with an increase in BMI for males but not for females. Sarcopenia was associated with a decrease in males but not in females. Having a stroke, more hospital admissions, and longer lengths of hospital stays were all associated with decreases in BMI among both males and females. Primary care visits were associated with a small increase in BMI for both sexes, but for only males was specialist visits associated with a small decrease in BMI. For females there was no association with specialist visits. Dying in the following year or in the current year was associated with large decreases in BMI. There was no association between percentage in poverty or median household income and BMI. Food environment (supermarkets, grocery stores, fast food restaurants, and convenience stores) and physical activity environment (parks and recreation areas, and public and commercial fitness facilities) measures had mostly insignificant associations with BMI

3. <u>Stratified regression results</u>

Table XVIII summarizes the marginal effects of mobility limitation on BMI at different levels of walkability, stratified by males and females and by residential movement, age group, and poverty tertiles. The values represent the effect of mobility limitation on BMI compared to not having mobility limitation at each walkability quartile, and with the average values for all other covariates in the model. For the model with all males, the effect of mobility limitation at walkability quartile one is 0.056 BMI units ($p<0.001$), and goes down to 0.042 BMI units ($p<0.001$) at walkability quartile two, and to 0.024 BMI units ($p<0.01$) at walkability quartile three, and 0.014 BMI units ($p=0.166$) and was no longer significant at walkability quartile four. For the model with all females, the effect of mobility limitation at walkability quartile one is 0.151 BMI units ($p<0.001$), and goes down to 0.118 BMI units ($p<0.01$) at walkability quartile two, and to 0.097 BMI units ($p<0.05$) at walkability quartile three, and 0.010 BMI units ($p=0.815$) at walkability quartile four, which was also no longer significant. The sections below describe each level of the stratified analysis.

a. <u>Residential movement</u>

In models where I stratified the sample by those who moved and those who stayed, there was a similar pattern of a lower effect of mobility limitation on BMI with increasing walkability. The effects for stayers better addresses the potential bias from residential self-selection, as the variation comes only from changes in the neighborhood and not from individual preferences..

TABLE XVII: FIXED-EFFECTS REGRESSION MODELS ESTIMATING INDIVIDUAL AND NEIGHBORHOOD EFFECTS ON BMI OF VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY FROM 2009-2014 [a,b]

	Males			Females		
	Person level only N=2,147,698	Person and environment variables N=2,145,006	Includes mobility limitation X walkability interaction N=2,145,006	Person level only N=174,616	Person and environment variables N=174,452	Includes mobility limitation X walkability interaction N=174, 452
Mobility limitation[c]	0.033***	0.033***	[d]0.056***	0.096***	0.096***	[d] 0.151***
	(0.006)	(0.006)	(0.010)	(0.027)	(0.027)	(0.040)
Mobility limitation X walkability quartile interaction (ref walkability quartile 1 & no mobility limitation)						
Mobility limitation X walkability quartile 2			-0.014			-0.033
			(0.011)			(0.043)
Mobility limitation X walkability quartile 3			-0.032*			-0.053
			(0.012)			(0.051)
Mobility limitation X walkability quartile 4			-0.043**			-0.141**
			(0.013)			(0.053)
Quan comorbidity score (ref=no comorbidities)						
Quan score 1-3	-0.058***	-0.058***	-0.058***	-0.152***	-0.151***	-0.151***
	(0.008)	(0.008)	(0.008)	(0.039)	(0.039)	(0.039)
Quan score >=4	-0.542***	-0.542***	-0.542***	-0.795***	-0.794***	-0.792***
	(0.016)	(0.016)	(0.016)	(0.105)	(0.105)	(0.105)
Age groups (ref = age 20-39)						
Age 40-49	0.504***	0.504***	0.504***	0.319***	0.318***	0.316***
	(0.026)	(0.026)	(0.026)	(0.053)	(0.053)	(0.053)
Age 50-64	0.758***	0.758***	0.758***	0.417***	0.414***	0.413***
	(0.030)	(0.030)	(0.030)	(0.066)	(0.066)	(0.066)
Age 65-74	0.772***	0.772***	0.772***	0.076	0.071	0.069

TABLE XVII: FIXED-EFFECTS REGRESSION MODELS ESTIMATING INDIVIDUAL AND NEIGHBORHOOD EFFECTS ON BMI OF VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY FROM 2009-2014 [a,b] (CONTINUED)

	Males			Females		
	Person level only N=2,147,698	Person and environment variables N=2,145,006	Includes mobility limitation X walkability interaction N=2,145,006	Person level only N=174,616	Person and environment variables N=174,452	Includes mobility limitation X walkability interaction N=174, 452
	(0.031)	(0.031)	(0.031)	(0.083)	(0.083)	(0.083)
Age 75-86	0.561***	0.561***	0.561***	-0.518***	-0.520***	-0.522***
	(0.032)	(0.032)	(0.032)	(0.118)	(0.118)	(0.118)
Year fixed effects (ref = 2010)						
Year=2011	-0.068***	-0.068***	-0.069***	0.050***	0.054***	0.054***
	(0.003)	(0.003)	(0.003)	(0.012)	(0.013)	(0.013)
Year=2012	-0.154***	-0.154***	-0.154***	0.082***	0.089***	0.089***
	(0.004)	(0.004)	(0.004)	(0.016)	(0.017)	(0.017)
Year=2013	-0.221***	-0.222***	-0.222***	0.126***	0.133***	0.133***
	(0.004)	(0.004)	(0.004)	(0.019)	(0.020)	(0.020)
Year=2014	-0.290***	-0.289***	-0.289***	0.242***	0.255***	0.256***
	(0.005)	(0.005)	(0.005)	(0.022)	(0.023)	(0.023)
Marital Status (ref = Married)						
Unknown marital	-0.129*	-0.130*	-0.130*	-0.076	-0.068	-0.067
	(0.052)	(0.052)	(0.052)	(0.173)	(0.173)	(0.173)
Separated/divorced	-0.027	-0.026	-0.026	-0.268***	-0.263***	-0.263***
	(0.016)	(0.016)	(0.016)	(0.062)	(0.061)	(0.061)
Widowed	-0.194***	-0.195***	-0.195***	-0.391**	-0.382**	-0.382**
	(0.024)	(0.024)	(0.024)	(0.126)	(0.126)	(0.126)
Single	-0.077***	-0.076***	-0.076***	-0.303***	-0.303***	-0.304***
	(0.018)	(0.018)	(0.018)	(0.072)	(0.072)	(0.072)
Health conditions, mortality and healthcare utilization						
Depression	0.048***	0.048***	0.048***	0.256***	0.257***	0.256***

TABLE XVII: FIXED-EFFECTS REGRESSION MODELS ESTIMATING INDIVIDUAL AND NEIGHBORHOOD EFFECTS ON BMI OF VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY FROM 2009-2014 [a,b] (CONTINUED)

	Males			Females		
	Person level only N=2,147,698	Person and environment variables N=2,145,006	Includes mobility limitation X walkability interaction N=2,145,006	Person level only N=174,616	Person and environment variables N=174,452	Includes mobility limitation X walkability interaction N=174, 452
	(0.012)	(0.012)	(0.012)	(0.042)	(0.042)	(0.042)
Substance abuse disorder	0.080***	0.081***	0.082***	0.081	0.080	0.082
	(0.014)	(0.014)	(0.014)	(0.078)	(0.078)	(0.078)
Sarcopenia	-0.664***	-0.665***	-0.665***	-0.560	-0.538	-0.541
	(0.058)	(0.058)	(0.058)	(0.338)	(0.339)	(0.339)
Stroke	-0.401***	-0.400***	-0.399***	-0.467***	-0.462***	-0.462***
	(0.021)	(0.021)	(0.021)	(0.132)	(0.132)	(0.132)
Hospital admissions	-0.197***	-0.197***	-0.197***	-0.179***	-0.179***	-0.179***
	(0.005)	(0.005)	(0.005)	(0.021)	(0.021)	(0.021)
Length of stay	-0.011***	-0.011***	-0.011***	-0.013***	-0.013***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Primary care encounters	0.002**	0.002**	0.002**	0.007*	0.007*	0.007*
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Specialty care encounters	-0.001***	-0.001***	-0.001***	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Died in following year	-0.750***	-0.750***	-0.750***	-0.831***	-0.834***	-0.833***
	(0.015)	(0.015)	(0.015)	(0.135)	(0.135)	(0.135)
Died in same year	-1.195***	-1.196***	-1.195***	-1.188***	-1.185***	-1.184***
	(0.017)	(0.017)	(0.017)	(0.140)	(0.140)	(0.140)
Neighborhood Poverty and Income						
% Below federal poverty line		-0.000	-0.000		-0.002	-0.002
		(0.000)	(0.000)		(0.001)	(0.001)

TABLE XVII: FIXED-EFFECTS REGRESSION MODELS ESTIMATING INDIVIDUAL AND NEIGHBORHOOD EFFECTS ON BMI OF VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY FROM 2009-2014 [a,b] (CONTINUED)

	Males			Females		
	Person level only N=2,147,698	Person and environment variables N=2,145,006	Includes mobility limitation X walkability interaction N=2,145,006	Person level only N=174,616	Person and environment variables N=174,452	Includes mobility limitation X walkability interaction N=174, 452
Median household income (per $1000)		0.002	0.002		0.005	0.005
		(0.002)	(0.002)		(0.009)	(0.009)
Walkability index within 1-mile (ref = Quartile 1)						
Quartile 2		-0.001	0.007		-0.001	0.018
		(0.008)	(0.010)		(0.028)	(0.038)
Quartile 3		-0.020*	-0.002		-0.064	-0.032
		(0.010)	(0.012)		(0.037)	(0.047)
Quartile 4		-0.043***	-0.019		-0.105*	-0.023
		(0.013)	(0.015)		(0.050)	(0.058)
Parks within 1-mile (ref = 0)						
1-2		-0.001	-0.001		-0.013	-0.013
		(0.009)	(0.009)		(0.032)	(0.032)
3-4		-0.024*	-0.024*		-0.028	-0.029
		(0.010)	(0.010)		(0.039)	(0.039)
5+		-0.002	-0.002		0.024	0.024
		(0.012)	(0.012)		(0.040)	(0.040)
Commercial fitness facilities within 1-mile (ref = 0)						
1-2		0.002	0.002		-0.008	-0.008
		(0.005)	(0.005)		(0.020)	(0.020)
3-6		0.016*	0.015*		-0.014	-0.014
		(0.007)	(0.007)		(0.030)	(0.030)
7+		0.005	0.005		-0.010	-0.010

TABLE XVII: FIXED-EFFECTS REGRESSION MODELS ESTIMATING INDIVIDUAL AND NEIGHBORHOOD EFFECTS ON BMI OF VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY FROM 2009-2014 [a,b] (CONTINUED)

	Males			Females		
	Person level only N=2,147,698	Person and environment variables N=2,145,006	Includes mobility limitation X walkability interaction N=2,145,006	Person level only N=174,616	Person and environment variables N=174,452	Includes mobility limitation X walkability interaction N=174, 452
		(0.006)	(0.006)		(0.027)	(0.027)
Supermarkets within 1-mile (ref=0)						
1		0.001	0.001		0.015	0.015
		(0.005)	(0.005)		(0.023)	(0.023)
2		0.008	0.008		-0.035	-0.035
		(0.007)	(0.007)		(0.029)	(0.029)
3+		0.000	0.000		-0.001	-0.002
		(0.006)	(0.006)		(0.025)	(0.025)
Convenience stores within 1-mile (ref = 0-1)						
2-5		0.003	0.003		0.038	0.038
		(0.007)	(0.007)		(0.027)	(0.027)
6-9		-0.004	-0.004		0.052	0.051
		(0.008)	(0.008)		(0.034)	(0.034)
10+		-0.001	-0.001		0.061	0.060
		(0.010)	(0.010)		(0.042)	(0.042)
Grocery stores within 1-mile (ref = 0)						
1		-0.001	-0.001		0.062**	0.062**
		(0.005)	(0.005)		(0.022)	(0.022)
2-5		-0.004	-0.004		0.039	0.037
		(0.009)	(0.009)		(0.037)	(0.037)
6+		-0.002	-0.002		0.032	0.032
		(0.005)	(0.005)		(0.021)	(0.021)
Fast food restaurants within 1-mile (ref = 0-4)						

TABLE XVII: FIXED-EFFECTS REGRESSION MODELS ESTIMATING INDIVIDUAL AND NEIGHBORHOOD EFFECTS ON BMI OF VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY FROM 2009-2014 [a,b] (CONTINUED)

	Males			Females		
	Person level only N=2,147,698	Person and environment variables N=2,145,006	Includes mobility limitation X walkability interaction N=2,145,006	Person level only N=174,616	Person and environment variables N=174,452	Includes mobility limitation X walkability interaction N=174, 452
5-10		0.002	0.002		0.027	0.027
		(0.007)	(0.007)		(0.027)	(0.027)
11-18		0.001	0.000		0.015	0.014
		(0.009)	(0.009)		(0.035)	(0.035)
19+		0.015	0.015		-0.068	-0.068
		(0.011)	(0.011)		(0.043)	(0.043)
Constant	29.301***	29.313***	29.299***	29.847***	29.842***	29.811***
	(0.029)	(0.035)	(0.035)	(0.067)	(0.100)	(0.101)
Adjusted R-squared	0.044	0.044	0.044	0.016	0.016	0.016

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

[a] Standard errors in parentheses, clustered on the subject and bootstrapped for the mobility limitation.

[b] Coefficients are reported from linear regressions with individual fixed effects.

[c] Mobility limitation is a predicted binary variable derived from a model in chapter one. The variable is lagged one-year.

[d] For the model that includes the mobility limitation X walkability interaction, the mobility limitation value represents the effect of a mobility limitation in walkability quartile one. The effect of mobility limitation on BMI in walkability quartiles two to four are relative to the effect of mobility limitation in walkability quartile one.

Among males, the effect of mobility limitation on BMI for movers changed very little from walkability quartile one to quartile three (0.045, p<0.01 to 0.041, p<0.01), and then decreased slightly for walkability quartile four (0.024, p=0.077). For stayers, however, the effect of a mobility limitation on BMI is highest in walking quartile one at 0.072 BMI units (p<0.001), and then reduces with each quartile until it is -0.006 BMI units (p=0.655) and is no longer significant in walkability quartile four.

Among females, the effect of mobility limitation on BMI for movers also changed very little from walkability quartile one to quartile three (0.110, p<0.05 to 0.157, p<0.01), but then decreases in walkability quartile four (0.018, p=0.741). For stayers, the effect of a mobility limitation on BMI is highest in walkability quartile one at 0.233 BMI units (p<0.001), and then reduces with each quartile until it is -0.013 BMI units (p=0.844) and is no longer significant in walkability quartile four.

b. Age groups

Among male veterans in age groups 20-39, the effects of mobility limitation across the first three walkability quartiles had similar effects, but walkability quartile four was lower and insignificant (-0.005, p=0.909). For Male veterans ages 40-49, there was a similar effect of mobility limitation on BMI across walkability quartiles. For veterans ages 50-64, there is evidence of a larger effect of mobility limitation on BMI at the lowest walkability quartile (0.044 unit BMI, p<0.01), and then a decreasing impact of mobility limitation at higher walkability quartiles and is 0.022 unit BMI (p=0.122) at walk quartile four. A similar pattern occurs for males in age groups 65-74 and 75+.

Among female veterans, there is a similar pattern of a lesser effect of mobility limitation on BMI at higher levels of walkability). Across age groups, those in the lower walkability quartiles had the higher effects of mobility limitation on BMI and those in the higher quartiles had the lowest effects of mobility limitation on BMI. However most of the coefficients for females were not significant at (p<0.05).

c. Census tract poverty

Among male veterans, living in high and medium poverty census tracts is associated with a larger effect of mobility limitation on BMI compared to those living in low-poverty census tracts. The effect of mobility limitation is 0.028 BMI units (p<0.05) in low-poverty neighborhoods and 0.101 BMI units (p<0.001) in high-poverty neighborhoods. Within each poverty level, the effect of mobility limitation on BMI decreases as walkability increases. Overall, the largest effect of mobility limitation on BMI for males is among those living in the highest poverty and lowest walkability neighborhoods (0.101 BMI units, p<0.001). For male veterans in the lowest poverty and highest walkability neighborhoods, a mobility limitation is associated with a decrease in BMI (-0.050 BMI units, p<0.05).

Among female veterans, there is a similar pattern. Within each poverty level, the effect of mobility limitation generally decreases as walkability increases. Overall, the largest effect of mobility limitation on BMI is among females in the medium poverty tertile and in the lowest walkability quartile (0.218 BMI units, p<0.01). For females living in the medium poverty tertile and highest walkability quartile, having a mobility limitation is associated with a decrease in BMI (-0.086 BMI units, p=0.246) and is no longer significant.

4. **Sensitivity analyses**

Table XIX shows the results of the four sensitivity analyses conducted in this study. For males, across the four sensitivity analyses, there were similar results as to what was seen in the original models. One exception was for the models with a quarter mile buffer for measuring walkability instead of a 1-mile buffer, where the effect of mobility limitation on BMI in walkability quartile four was larger and still significant than walkability quartile four for the 1-mile buffer. This may have to do with the distributions of the walkability values differing between the 1-mile buffer vs. quarter mile buffer. Nonetheless, there remained a similar pattern between each buffer, where the highest effect was in walkability quartile one and there was a lower effect was in quartile four.

Among females, there were also similar results across sensitivity tests. The alternative cut-off model had slightly lower effects of mobility limitation on BMI in all of the walkability quartiles, but there was a similar pattern of a decreasing effect with increasing walkability. The smaller effect makes sense in that changing the cut-off changes the cohort by reclassifying some as having no mobility limitation. Those who were reclassified are the ones who had lower predicted values that were close to the cut-off.

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TABLE XVIII: AVERAGE MARGINAL EFFECTS FROM FIXED-EFFECTS REGRESSION MODELS OF MOBILITY LIMITATION ON BMI ACROSS FOUR QUARTILES OF WALKABILITY, STRATIFIED BY MALES AND FEMALES AND BY RESIDENTIAL MOVEMENT, AGE GROUPS, AND CENSUS TRACT POVERTY TERTILES FOR VETERANS IN THE WAVES STUDY 2009-2014 [a,b,c]

	Males N= 2,145,015				**Females** N= 174,456			
Walkability Quartiles	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Fixed-effects regression model with interaction for the full sample	0.056***	0.042***	0.024**	0.014	0.151***	0.118**	0.097*	0.010
	(0.010)	(0.009)	(0.009)	(0.010)	(0.039)	(0.038)	(0.039)	(0.043)
Residential movement[d]								
Mover	0.045**	0.046***	0.041**	0.024	0.110*	0.138**	0.157**	0.018
	(0.014)	(0.013)	(0.013)	(0.014)	(0.051)	(0.049)	(0.05)	(0.055)
Stayer	0.072***	0.036**	0.000	-0.006	0.233***	0.078	-0.028	-0.013
	(0.013)	(0.012)	(0.013)	(0.014)	(0.061)	(0.057)	(0.063)	(0.067)
Age groups								
20-39	0.080*	0.089*	0.081*	-0.005	0.112	0.044	0.114	-0.081
	(0.039)	(0.038)	(0.039)	(0.044)	(0.074)	(0.071)	(0.073)	(0.088)
40-49	0.093**	0.033	0.085**	0.078*	0.171*	0.114	0.068	0.138
	(0.031)	(0.031)	(0.032)	(0.033)	(0.076)	(0.077)	(0.083)	(0.083)
50-64	0.044**	0.038**	0.023	0.022	0.091	0.120*	0.065	-0.002
	(0.015)	(0.014)	(0.014)	(0.014)	(0.066)	(0.061)	(0.067)	(0.068)
65-74[e]	0.077***	0.020	-0.047*	-0.039	0.221	0.284*	0.110	-0.147
	(0.018)	(0.018)	(0.018)	(0.02)	(0.135)	(0.14)	(0.104)	(0.128)
75+	0.047*	0.019	-0.003	-0.049				
	(0.023)	(0.022)	(0.023)	(0.025)				
Poverty tertiles[f]								
Low-poverty	0.028*	0.020	-0.016	-0.050*	0.120*	0.130	0.098	0.039
	(0.014)	(0.014)	(0.016)	(0.022)	(0.061)	(0.068)	(0.071)	(0.103)

TABLE XVIII: AVERAGE MARGINAL EFFECTS FROM FIXED-EFFECTS REGRESSION MODELS OF MOBILITY LIMITATION ON BMI ACROSS FOUR QUARTILES OF WALKABILITY, STRATIFIED BY MALES AND FEMALES AND BY RESIDENTIAL MOVEMENT, AGE GROUPS, AND CENSUS TRACT POVERTY TERTILES FOR VETERANS IN THE WAVES STUDY 2009-2014 [a,b,c] (CONTINUED)

	Males N= 2,145,015				**Females** N= 174,456			
Walkability Quartiles	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Med poverty	0.078***	0.052**	0.013	0.014	0.218**	0.189**	0.157*	-0.086
	(0.018)	(0.016)	(0.017)	(0.019)	(0.071)	(0.064)	(0.069)	(0.074)
High-poverty	0.101***	0.060***	0.061***	0.028*	0.127	0.043	0.009	0.054
	(0.022)	(0.018)	(0.016)	(0.014)	(0.081)	(0.068)	(0.067)	(0.063)

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

[a] Marginal effects are estimated for average values of covariates used in the fixed-effects regression model of mobility limitation on BMI including Quan Comorbidity group, age categories, year fixed effects, marital status, depression, substance abuse disorder, stroke, hospitalization, length of stay, primary care visits, specialist care visits, dying, died, census tract percent in poverty, census tract median household income, and quartiles of parks, physical activity facilities, supermarkets, convenience stores, grocery stores, and fast food restaurants.

[b] Standard errors in parentheses, clustered on the subject.

[c] Mobility limitation is a predicted binary variable derived from a model in chapter one. The variable is lagged one-year.

[d] Residential movement was split into those who moved at least once during 2009-2014 and those who never moved during that time.

[e] Females in age groups 65-74 and 75+ were combined because of lower sample sizes in those age ranges.

[f] Poverty tertiles were developed from a measure of census tract percentage below the federal poverty line.

These may be the individuals who are increasing in BMI, and so when reclassified, the overall effect of mobility limitation for females was reduced.

Table XX compares the main findings that used the binary mobility limitation variable with findings from the categorical mobility limitation variable that separated the sample into ‘no mobility limitation, ‘possible mobility limitation’, and ‘high likelihood of mobility limitation’. There are two sets of results for the categorical variable with no mobility limitation as the reference and interaction with walkability. In the models without interactions, the results for the possible mobility limitation group are similar in magnitude to the original binary variable, whereas the results for the high likelihood of mobility limitation variable are slightly lower for males (0.021 BMI units ($p<0.001$) compared to 0.036 BMI units ($p<0.05$)) and far lower for females (0.035 ($p=0.305$) compared to 0.097 ($p<0.001$). In the model with an interaction between mobility limitation and walkability, both the possible and high likelihood groups show a significant difference for the effect of mobility limitation on BMI between the low-walkability quartile to the high walkability quartile. The effect is reduced by a larger difference for the high likelihood group. For males in the possible mobility limitation group, the effect of mobility limitation on BMI is 0.052 ($p<0.001$) in walkability quartile one and at walkability quartile four, there is a difference of 0.029 ($p<0.05$). However, for the high likelihood group, there is an increase of 0.057 BMI units ($p<0.001$) at walkability quartile one, which reduces by 0.071 BMI units ($p<0.001$) difference relative to walkability quartile one. There is a similar pattern for females for both the possible and high likelihood of a mobility limitation groups.

E. <u>Discussion</u>

Obesity is even more prevalent among people with mobility limitations than among those without (An et al., 2015; Reichard et al., 2011). Given the many consequences of obesity for later life health and quality of life as well as its potential to worsen mobility limitation itself, finding ways to help people avoid obesity is an important public health goal (Fox et al., 2013; Krahn et al., 2015).

TABLE XIX: SENSITIVITY ANALYSIS OF FIXED-EFFECTS REGRESSION MODELS OF THE EFFECT OF MOBILITY LIMITATION ON BMI ACROSS QUARTILES OF WALKABILITY FOR VETERANS IN THE WAVES STUDY 2009-2014

	Males N=2,136,498				**Females** N=174,207			
Walkability Quartiles	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Fixed-effects model with interaction from main analysis	0.056***	0.042***	0.024**	0.014	0.151***	0.118**	0.097*	0.010
	(0.010)	(0.009)	(0.009)	(0.010)	(0.039)	(0.038)	(0.039)	(0.043)
Sensitivity analyses								
Quarter mile buffer[a]	0.054***	0.045***	0.002	0.034***	0.116**	0.153***	0.069	0.037
	(0.009)	(0.009)	(0.009)	(0.01)	(0.039)	(0.036)	(0.037)	(0.043)
Alternative cut-off[b]	0.058***	0.046***	0.028**	0.016	0.123**	0.067	0.062	-0.031
	(0.01)	(0.009)	(0.009)	(0.01)	(0.04)	(0.038)	(0.039)	(0.043)
No paraplegia/ quadriplegia[c]	0.057***	0.042***	0.024**	0.013	0.150***	0.120**	0.097**	0.012
	(0.01)	(0.009)	(0.009)	(0.01)	(0.039)	(0.038)	(0.039)	(0.043)
No other environmental variables[d]	0.056***	0.042***	0.024**	0.014	0.152***	0.118**	0.097*	0.010
	(0.009)	(0.009)	(0.009)	(0.01)	(0.039)	(0.038)	(0.039)	(0.043)

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

Marginal effects are estimated for average values of covariates used in the fixed-effects regression model of mobility limitation on BMI, including Quan Comorbidity group, age categories, year fixed effects, marital status, depression, substance abuse disorder, stroke, hospitalization, length of stay, primary care visits, specialist care visits, dying, died, census tract percent in poverty, census tract median household income, and quartiles of parks, physical activity facilities, supermarkets, convenience stores, grocery stores, and fast food restaurants.

Alternative models tested were using:
[a] Quarter mile buffer instead of a 1-mile buffer for walkability measure.

[b] A different cut-off that used 5% higher specificity for creating a binary mobility limitation variable from a predicted model in chapter one.

[c] Exclusion of veterans with paraplegia or quadriplegia whose weight may be inaccurate.

[d] Food and physical activity environment variables were excluded to examine duplication of values in the walkability index.

TABLE XX: SENSITIVITY ANALYSIS COMPARING OUTCOMES FROM FIXED-EFFECTS REGRESSION MODELS FOR A BINARY MOBILITY LIMITATION VARIABLE AND A CATEGORICAL MOBILITY LIMITATION VARIABLE FOR VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY, 2009-2014 [a,b,c]

	Males		Females	
	Person and Environment variables	**Includes mobility limitation X walkability interaction**	**Person and Environment variables**	**Includes mobility limitation X walkability interaction**
Binary mobility limitation variable	0.036***	0.056***	0.097***	0.151***
	(0.006)	(0.010)	(0.025)	(0.040)
Mobility limitation X walk quartile interaction (ref Walk quartile 1 & No mobility limitation)				
Mobility limitation X walkability quartile 2		-0.014		-0.033
		(0.011)		(0.043)
Mobility limitation X walkability quartile 3		-0.032*		-0.053
		(0.012)		(0.051)
Mobility limitation X walkability quartile 4		-0.043**		-0.141**
		(0.013)		(0.053)
Alternative categorical mobility limitation variable				
Mobility limitation X walk quartile interaction (ref Walk quartile 1 & No mobility limitation)				
Possible mobility limitation	0.039***	0.052***	0.110***	0.153***
	(0.006)	(0.009)	-0.026	-0.041
Possible mobility limitation X walkability quartile 2		-0.012		(0.036)
		(0.012)		-0.047
Possible mobility limitation X walkability quartile 3		-0.020		(0.032)
		(0.013)		-0.054
Possible mobility limitation X walkability quartile 4		-0.029*		-0.112*
		(0.014)		(0.057)
High likelihood of mobility limitation	0.021*	0.057***	0.035	0.108

TABLE XX: SENSITIVITY ANALYSIS COMPARING OUTCOMES FROM FIXED-EFFECTS REGRESSION MODELS FOR A BINARY MOBILITY LIMITATION VARIABLE AND A CATEGORICAL MOBILITY LIMITATION VARIABLE FOR VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY, 2009-2014 [a,b,c] (CONTINUED)

	Males		**Females**	
	Person and Environment variables	**Includes mobility limitation X walkability interaction**	**Person and Environment variables**	**Includes mobility limitation X walkability interaction**
	(0.009)	(0.013)	-0.035	-0.056
High likelihood of mobility limitation X walkability quartile 2		-0.020		(0.032)
		(0.016)		-0.057
High likelihood of mobility limitation X walkability quartile 3		-0.057***		-0.090
		(0.017)		(0.070)
High likelihood of mobility limitation X walkability quartile 4		-0.071***		-0.188**
		(0.019)		(0.073)

[a] Covariates used in the fixed-effects regression model of mobility limitation on BMI include Quan Comorbidity group, age categories, year fixed effects, marital status, depression, substance abuse disorder, stroke, hospitalization, length of stay, primary care visits, specialist care visits, dying, died, census tract percent in poverty, census tract median household income, and quartiles of parks, physical activity facilities, supermarkets, convenience stores, grocery stores, and fast food restaurants.

[b] Standard errors in parentheses, clustered on the subject and bootstrapped for the mobility limitation.

[c] Mobility limitation is a predicted variable derived from a model in chapter one. The variable is lagged one-year.

Although research has suggested that neighborhood walkability may play an important role in helping to curb the obesity epidemic in the US population (Chandrabose et al., 2019; Sallis et al., 2012), there is no existing research on how neighborhood walkability impacts body weight for people with mobility limitations.

1. **Neighborhood environment moderation**

In this study, I examined if and how the effect of mobility limitation on BMI changes from low - high walkability neighborhoods. I found that neighborhood walkability moderated the effect of mobility limitation on BMI. Specifically, mobility limitation was associated with an increase in BMI in the lowest walkability neighborhoods (0.056 BMI units ($p<0.001$) for males and 0.151 BMI units ($p<0.001$) for females), but in high-walkability neighborhoods, mobility limitation was no longer associated with BMI (0.014 BMI units 0.166 for males and 0.010 BMI units $p=0.815$ for females). Additionally, the results showed how low-walkability neighborhoods can exacerbate the effect of mobility limitation on BMI for people living in high-poverty neighborhoods, as the largest effect of mobility limitation on BMI among all subgroups was for those living in the highest poverty tertile. Finally, the pattern of moderation held across age groups, although the pattern was more apparent among older adults. These results suggest that living in a high-walkability neighborhood has a protective factor that diminishes the effect of mobility limitation on weight gain, and that living in low-walkability neighborhoods may negatively affect people with mobility limitations through greater increases in BMI.

A major threat to causal interpretation of walkability affecting BMI as well as the interaction effect with mobility limitation is not accounting for residential self-selection, which is the selection bias of people who are already physically active moving to neighborhoods that are more walkable (Handy et al., 2006; Mayne et al., 2015; McCormack & Shiell, 2011). An individual's preference for a more walkable neighborhood was a personal characteristic addressed by the inclusion of individual fixed effects. In other words, the individual fixed-effects model captures individual preferences that are fixed over time and which may have led to a person moving to a highly walkable neighborhood before the time period studied in this chapter. However, if an individual's preferences changed during the study period and the subject moved residences for reasons related to mobility limitation and BMI, that could bias the internal validity of the results. An example is an individual who became disabled and then moved to a more walkable neighborhood because of loss of an ability to drive or the desire to be able to walk to nearby destinations to improve their health. Similar to previous analysis using WAVES data (Zenk et al., 2017), I addressed the potential for change in individual's preferences for walkable neighborhoods by stratifying the analysis according to movers and stayers. For stayers, the variation in neighborhood walkability comes from the opening or closing of neighborhood destinations, changes in population or housing density, and improvements to street connectivity, although these occur less often (Zenk et al., 2018). Thus, there is less of a threat of time-varying omitted variable bias related to residential self-selection because individuals have less impact on changes in the environment. The results from this study were further strengthened by the fact that for stayers (those who never moved residences), there was a similar pattern of moderation of the effect of mobility limitation on BMI.

Despite these efforts, there may be time-varying unobserved variables that were not controlled for in this study, and that could be correlated with mobility limitation, walkability, and BMI. Data on individual income were not available for this study. Individual income may be an important unmeasured variable, as higher income is associated with physical activity, weight change, where people live, and healthcare coverage—all of which can be associated with mobility limitation, neighborhood walkability, and BMI. Although we used individual fixed-effects models, a change in individual-level income, which we are not able to observe, would threaten the internal validity. That is, a reduction in income could be the result of a mobility limitation but also affect an individual's eating habits and perhaps the types of restaurants and food stores where a person shops. Such a change in consumption would be an example of a time-varying covariate that would not be controlled for by the individual fixed effects.

Another unobserved factor is that the additional walking done in high-walkability neighborhoods can improve mobility functioning by strengthening muscles used during walking activity. In high-walkability neighborhoods, mobility limitation may be less likely to become more severe over time (Clarke, Ailshire, Bader, Morenoff, & House, 2008). Preventing further mobility limitation could also support the maintenance of existing levels of physical activity and subsequent changes in BMI. I was not able to address change in the level of mobility limitation as a binary mobility limitation variable was used. Future work that is able to utilize a multi-level mobility limitation variable could help to address this threat to internal validity.

2. **Contribution**

To my knowledge, this is the first study to explore the role of the neighborhood environment in moderating the effect of mobility limitation on BMI. I leveraged a longitudinal panel dataset of a nationwide sample of veterans living in large central metropolitan counties with wide geographic diversity. I utilized a novel mobility limitation algorithm to identify a large group of veterans with mobility limitation. Lastly, the measurement of BMI from WAVES was based on clinical measurements of height and weight, and so is less biased then self-reported BMI.

The findings were robust to the sensitivity analyses conducted in this study that tested alternative specifications of both mobility limitation and walkability variables. Most informative is the alternative specification that used a categorical mobility limitation variable with three groups for no mobility limitation, possible mobility limitation, and high likelihood of mobility limitation. Because the mobility limitation algorithm was highly sensitive, it may be over-classifying people with mobility limitations (i.e. too many false positives). Results from the categorical version of mobility limitation address the possibility that false positives were driving the results in the binary version of mobility limitation and not the true positive group. The results showed that the pattern of walkability moderating the effect of mobility limitation on BMI held for those who are highly likely to have a mobility limitation and even showed a larger difference in the effects between walkability quartile four relative to one.

Considering reasons for why walkability moderated the effect of mobility limitation on BMI, one explanation is that people with mobility limitations in the high-walkability neighborhoods change their walking/rolling behavior, and so they are not gaining as much weight as they would have otherwise. A constant level of physical activity would be controlled for with the individual level fixed effects, but a change in physical activity patterns would be a time-varying unobserved factor that would not be controlled for by the individual fixed effects. At the same time, it may be the case that people with mobility limitations in low-walkability neighborhoods change their activity patterns and become more sedentary compared to those without. Thus, the effect of mobility limitation on BMI is considerably higher in those neighborhoods. I was unable to test this supposition with the available data, but it is consistent with other studies that showed that living in high walkability neighborhoods was associated with increased physical activity for individuals with mobility limitation (King et al., 2011; Satariano et al., 2010; Van Holle et al., 2016).

3. **Findings on moderation in the context of previous literature**

Overall, the magnitude of the effect of mobility limitation on BMI was not large. Based on a 0.033 unit BMI increase for males and 0.096 unit BMI increase for females (see Table XVII models without interactions), we would predict a mobility limitation to lead to a 0.22 pound weight decrease for a 5-foot 10-inch male and a 0.56 pound weight decrease for a 5-foot 5-inch female. While this decrease in weight is not considered clinically meaningful based on a 5% weight change (Foster et al., 2004), small reductions in weight over time may reduce the risk of mortality, heart disease, and further disability (Aune et al., 2016; Collaborators, 2017). In other words, being in a high-walkability neighborhood and not gaining weight as a result of a mobility limitation can have positive health benefits.

Although the magnitude was small, results from this study suggest that neighborhood walkability is an important contextual factor that can alter the relationship between mobility limitation and BMI. These findings support the WHO's ICF model (World Health Organization, 2001) by showing the role of contextual factors as moderators of mobility limitation. The contextual factors included in this study had to do with environmental factors (walkability, poverty, residential movement) and personal factors (age). Modeling contextual factors was made possible by leveraging a large national dataset of veterans that was assembled in WAVES and included both person-level and neighborhood-level covariates.

I found that for both male and female stayers, the higher the walkability, the smaller the effect of mobility limitation on BMI. At walkability quartile four, there was no effect of mobility limitation on BMI for both males and females. For movers, the pattern was similar, where those in the highest walkability quartile had the lowest effect of mobility limitation on BMI, and the lowest quartile had the highest effect, but there was a similar degree of magnitude for the first three walkability quartiles. It was not until the last, highest walkability quartile that the effect of mobility limitation lessened compared to the first three quartiles. No previous studies have examined the interaction effect of mobility limitation and walkability on BMI for movers versus stayers. Previous research that examined the interaction effect between mobility limitation and walkability on physical activity (King et al., 2011; Satariano et al., 2010; Van Holle et al., 2016) were cross-sectional and so did not stratify by movers and stayers, or address residential self-selection in any other way. In a previous study on walkability using WAVES, high-walkability was associated with lower BMI for movers compared to stayers when all ages were combined (Tarlov et al., 2019). The difference in this chapter is the inclusion of an interaction term with mobility limitation and walkability. The effects for stayers in this study evidence a causal moderating effect of walkability that comes from store openings and closings, instead of an individual moving residences. The larger effects for stayers found in this study may also point to the impact of sustained exposure to a low or high-walkability area for those with mobility limitations. Stayers may be more familiar with their neighborhood and thus more likely to walk/roll even though they have a mobility limitation. Conversely, people who develop a mobility limitation and are always in a lower walkability neighborhood (reference group) may have a perception that walking/rolling is not possible in their neighborhoods, or that it is dangerous because of the lack of safe sidewalks and crossings (Rosenberg et al., 2013). This perceived fear may further limit and deter walking/rolling, leading to greater physical inactivity and potential for increased BMI.

4. **Differential outcomes by age group**

Additionally, this study found a different effect of neighborhood walkability and mobility limitation on BMI by age group. Among males in all age groups, the largest effect of mobility limitation on BMI was in the lowest walkability quartile. There was a similar pattern for females, but estimates were mostly not significant. These findings suggest that lower walkability neighborhoods may have a deleterious effect on BMI among veterans with mobility limitations across ages. Tarlov et al. (2019) used the WAVES dataset to study walkability across age groups and found higher walkability was associated with a decrease in BMI among middle aged males 30-64, but not for those below 30 or above age 75. Two previous studies on walkability and BMI that included mobility limitation only focused on older adults greater than age 65 (King et al., 2011; Michael et al., 2014) and did not address age-related difference in the effect of mobility limitation on BMI at different levels of walkability. In the second chapter of this dissertation, I showed that mobility limitation was associated with increased BMI at younger ages. Findings in the current chapter suggest that for younger adults, neighborhood walkability may play a role in moderating the effect of mobility limitation on BMI, as the effect was no longer significant in highest walkability neighborhoods. This analysis also showed that for older ages (age 50+), living in lower walkability neighborhoods and having a mobility limitation can lead to increases in BMI, whereas older adults (generally at age 60) maintain their BMI and then begin to have decreases in BMI (Stenholm et al., 2015). Additionally, in chapter two of this dissertation, I showed that for those aged 65-74, mobility limitation had a very small effect for males and no effect for females, and for those 75+, mobility limitation was not associated with BMI. These findings suggest that living in a low-walkability neighborhood and developing a mobility limitation at an older age may be risk factors for increased BMI. Because older adults may be driving less or not at all (Liddle & McKenna, 2003), having a mobility limitation in low-walkability neighborhoods could lead to further isolation and limit options for leaving the home and engaging in neighborhood walking activity.

5. **Compounding effect of neighborhood poverty**

Another important finding from this study was the role of neighborhood poverty. Neighborhood SES has been shown to moderate the effect of walkability on BMI, with lower SES neighborhoods being associated with increases in BMI (Lovasi et al., 2009; Rundle et al., 2008). I examined whether the effect of mobility limitation on BMI varied by different combinations of walkability and SES; I found that the effect of having a mobility limitation and being in a low-walkability neighborhood is greater among people living in high-poverty areas. The salubrious effects of living in a high-walkability area (e.g. lower BMI) are obtained only among those living in low-poverty areas. Similar results were found for females.

These results for BMI differed from a previous study that looked at how mobility limitation interacts with walkability and SES to impact physical activity. Van Holle et al. (2016) found that being in a high income, high-walkability neighborhood was associated with higher physical activity for people with mobility limitations, but that there was no difference in physical activity in low-income neighborhoods no matter the level of walkability. However, with respect to BMI, I found that even in high-poverty neighborhoods, the effect of mobility limitation on BMI still decreased as walkability increased, although never led to lower BMI. Besides having a different outcome than Van Holle et al. (2016), their study was cross-sectional, whereas my study leveraged longitudinal data and individual fixed effects to account for time-invariant unobserved variables. The fact that walkability still modified the effect of mobility limitation on BMI in high-poverty neighborhoods supports policy and environmental interventions to improve walkability in high-poverty neighborhoods despite additional challenges high-poverty neighborhoods present to neighborhood walking. This is especially important when we consider that there has been a steady national trend of poverty moving from urban areas to suburban areas over the last two decades (Kneebone, 2019), and that people with mobility limitations are also more likely to be in poverty (Iezzoni et al., 2001; Lauer & Houtenville, 2018; Palmer, 2011).

The high-poverty neighborhoods studied in this chapter may be capturing certain aspects of the physical and social environment that affect walking activity. For instance, areas that have a high rate of poverty are negatively associated with neighborhood attractiveness (Handy et al., 2006; Saelens & Handy, 2008) and positively associated with crime (Hsieh & Pugh, 1993), both of which can affect walking activity. Because of these factors, a high-walkability neighborhood that is also impoverished may not be perceived as highly walkable. People with mobility limitations may have even greater fears about walking in unsafe areas, as research has shown that people with mobility limitations are more likely to be victims of violence (Breiding & Armour, 2015; Hughes et al., 2012; Powers & Oschwald, 2004). It is possible that these perceptions of walkability and safety increase physical inactivity and subsequent increases in BMI in high-poverty neighborhoods.

Interestingly, among males, there are similar effect sizes between those who are in high-poverty, high-walkability neighborhoods and low-poverty, low-walkability neighborhoods (both at 0.028 BMI units, $p<0.05$). This similarity suggests that living in low-walkability neighborhoods still has an impact on BMI that is sustained even in areas where poverty is not a concern. Because the male sample in this study is older, these effects may again be reflecting the combination of mobility limitation and limitations in driving for those who live in low-walkability areas.

6. **Further policy implications**

In low-walkability areas, reconstructing the street network is often not a possibility. However, there have been various initiatives by urban planners to develop the walkability of downtown areas. Rezoning certain areas to have a mixture of uses has been used to increase walkability so that there are more destinations nearby (Herndon, 2011). As the US population ages, there has been a growing interest in age-friendly cities and neighborhoods, and walkability has been a tenet of those initiatives (American Association of Retired Persons, 2019). Such initiatives could potentially benefit people with mobility limitations through the prevention of increased BMI associated with higher walkability neighborhoods.

The larger effect of mobility limitation on BMI in high-poverty neighborhoods supports the need for policies and environmental interventions to improve walkability in low income areas. A caution that previous research has pointed out is that improving walkability is sometimes also accompanied by gentrification of a neighborhood (Combs, 2015). Increased destinations can make the neighborhood more attractive to those with more disposable income. Higher rents or conversions of apartment buildings to condominiums then push poorer residents out. Gentrification has been part of the reason for the shift of poverty to suburban areas (Kneebone, 2019).

Finally, there may be implications for housing policies. Local and regional housing agencies that provide affordable housing for people with mobility limitations could consider walkability as a part of the criteria they use to both match people to certain housing and to determine where new housing is going to be developed. For instance, in Illinois, the Illinois Housing Development Authority developed an ‘opportunity zone’ approach that designated certain areas of communities as higher importance, and so developers get higher scores by proposing projects in those areas (Illinois Department of Commerce & Economic Opportunity, 2019). These designated areas are based on various factors related to neighborhood SES, but walkability is not one of them. The options for moving to accessible housing are more limited and are often in lower income neighborhoods (National Council on Disability, 2010). Results from this study regarding the role of walkability suggest that considering walkability in designating housing opportunity zones could have positive health benefits for clients with mobility limitations.

F. Limitations

This study was not without limitations. I did not address barriers to the accessibility of the pedestrian environment that may further influence walking behavior among people with mobility limitations (Kirchner et al., 2008; Rosenberg et al., 2013). Data on barriers, such as broken or missing sidewalks, lack of curb ramps, and dangerous intersections are not readily available and most often require very detailed data collection, which was not possible as part of this secondary data analysis. Future research that had access to such micro-level data on barriers could be linked to the WAVES data to examine how such barriers affect the relationship between mobility limitation and BMI.

In this study, I used a binary mobility limitation variable because of limitations in the types of data that are available related to mobility limitation severity and challenges to developing a multi-level mobility limitation algorithm described in chapter one of this dissertation. It is possible that neighborhood walkability affects BMI only for people with certain levels of mobility limitation. Previous research has shown that the effect of walkability on physical activity was only significant for those with mild mobility limitation (King et al., 2011; Satariano et al., 2010; Van Holle et al., 2016). The findings from these previous studies suggest that the reduction in BMI observed in this study may be coming primarily from people with mild mobility limitations, and that those with more severe mobility limitations may not be as affected by the level of walkability of a neighborhood. Future research can build off this study and conduct a similar analysis with a multi-level mobility limitation variable. Also, the mobility limitation algorithm was limited in that it was developed from a relatively small sample (n=964) of only Medicare beneficiaries, and has not been validated beyond that sample.

Another limitation to generalizability is that veterans in this study are only those who utilize the VHA. A report on the VA estimated that in 2014, only 42% of all veterans were enrolled in the VA healthcare, and between 63% - 65% of those enrolled actually used VA healthcare (Bagalman, 2014). VHA users may be more likely to be lower income, unemployed, older, and have lower health status (Liu et al., 2005; Nelson et al., 2007). Also, veterans may be different in their patterns of healthcare utilization that are unique to the health plans and benefits available through the VHA. Since this study was based on healthcare administrative data from the VHA, use of similar data for non-veterans may show different results. Given the extensive sensitivity analysis and what might be considered over-sampling of those with mobility limitations due to the use of VHA for assistive devices, it can be argued that findings in other settings are not likely to be substantially different.

G. Conclusion

Findings from this study suggest that neighborhood walkability is an important contextual factor to better understand the relationship between mobility limitation and BMI. Living in high-walkability neighborhoods supports people with mobility limitations in maintaining their weight. However, being in low-walkability neighborhoods can further increase the effect of mobility limitation on BMI, especially among those older in age and those in high-poverty areas. The approaches used in this study to address threats to causality strengthen the findings. Future studies on mobility limitation, walkability, and BMI could benefit from similar approaches. Because people with mobility limitations represent a significant proportion of the population, strategies, such as improving walkability may have important public health benefits. As communities plan and design improvements to the walkability of neighborhoods, they should seek to identify and prioritize walkability improvements for areas with a high percentage of people with mobility limitations. Doing so has the potential to prevent increases in BMI related to living in low-walkability areas that were found in this study for a large segment of the US population.

APPENDICES

APPENDIX A

TABLE XXI: NPPD GROUPS AND NPPD[A] LINES USED BY THE VHA IN CODING ALL PROSTHETIC DEVICES PROVIDED BY THE PROSTHETICS SERVICE (DEPARTMENT OF VETERANS AFFAIRS, 2014)

NPPD Group	NPPD Line
New Activities	
WHEELCHAIRS AND ACCESSORIES	100 A MOTORIZED 100 A1 SCOOTERS 100 B MANUAL CUSTOM 100 C STANDARD 100 D W/C ACCESSORIES 100 E CUSHION 100 F CUSHION CUSTOM 100 G CARRIERS 100 H NSC VAN MODS 100 I SCOOTER ACCESSORIES
ARTIFICIAL LEGS	200 A LEG IPOP 200 B LEG TEM 200 C LEG PART FOOT 200 E LEG SYMES 200 F LEG B/K 200 G LEG A/O 200 H LEG A/K 200 I LEG COMPONENT
ARTIFICIAL ARMS / TERMINAL DEV	300 A ARM B/E 300 B ARM A/E *300 C COSMETIC GLOVES 300 D ARM A/O 300 E TERMINAL DEVICE 300 F EXT PWR ARM A/O EXT PWR TRM D *Not active
ORTHOSIS/ORTHOTICS	400 A ORTHOSIS ANKLE 400 B ORTHOSIS LEG A/K 400 C ORTHOSIS, SPINAL 400 D ORTHOSIS AL/OTH 400 E COMP HOSE/BURN GARMENT 400 F ORTHOSIS, KNEE *400 G CORSET/BELT 400 H ORTHOSIS, WHO 400X ORTHOSIS UNKNOWN *Not active
SHOES/ORTHOTICS	500 A FOOT ORTHOSIS/INSERTS/ARCH SUPPORTS 500 B SHOE NON CUSTOM 500 C SHOE CUSTOM *500 D SHOE ORTH OTH *500 E INSERTS, SHOE *500 F SHOES A/O *Not active

APPENDIX A (continued)

TABLE XXI: NPPD GROUPS AND NPPD[A] LINES USED BY THE VHA IN CODING ALL PROSTHETIC DEVICES PROVIDED BY THE PROSTHETICS SERVICE (DEPARTMENT OF VETERANS AFFAIRS, 2014) (CONTINUED)	
NPPD Group	**NPPD Line**
SENSORI-NEURO AIDS	600 1 EYEGLASSES 600 A NO LONGER USED 600 B HEARING AIDS 600 C AID FOR BLIND 600 D CONT LENS 600 E EAR INSERT/MOLD 600 F ASST LISTENING DEVICES 600 G SPEECH DEVICES
RESTORATIONS	700 A EYE 700 B FACIAL 700 C BODY, OTHER
OXYGEN AND RESPIRATORY	800 A OXYGEN EQP 800 B OXYGEN CONCEN 800 C MOVED TO REPAIR 800 D OXYGEN, SUPPLIES 800 E MOVED TO REPAIR 800 F VENTILATOR, A/O 800 G RESPIRATORY EQUIPMENT 800 H RESPIRATORY SUPPLIES
MEDICAL EQUIPMENT	900 A WALKING AIDS 900 B PATIENT LIFT 900 C BED HOSP STD 900 D BED HOSP SPEC 900 E MATTRESS STAN 900 F MATTRESS SPEC 900 G BED, ACCESSORIES 900 H ENVIRON CONTROL 900 I HOME SAFETY EQUIP 900 J NO LONGER USED 900 K MED EQP AL/OTH 900 L NO LONGER USED 900 M COMPUTER EQUIPMENT 900 N TELEHEALTH 900 O EXERCISE EQUIPMENT 900 P WOMENS HEALTH
ALL OTHER SUPPLIES AND EQUIP	910 A MED SUP AL/OTH 910 B BATTERIES
HOME DIALYSIS PROGRAM	920 A HOME DIAL EQP 920 B HOME DIAL SUP
ADAPTIVE EQUIPMENT	*930 A MOD VANS *930 B ADAPT EQP ALL/OTHER * Not active
HISA	940 A SC 940 B NSC
CLOTHING ALLOWANCE	*950 A APPROVED *950 B DISAPPROVED *Not active

APPENDIX A (continued)

TABLE XXI: NPPD GROUPS AND NPPD[A] LINES USED BY THE VHA IN CODING ALL PROSTHETIC DEVICES PROVIDED BY THE PROSTHETICS SERVICE (DEPARTMENT OF VETERANS AFFAIRS, 2014) (CONTINUED)

NPPD Group	NPPD Line
SURGICAL IMPLANTS	960 A H&N ALL OTHER 960 A1 H&N INTRAOCULAR LENS 960 A2 H&N HEAD 960 A3 H&N NECK 960 A4 H&N EYES A/O 960 B ABDOMEN ALL OTHER 960 B1 ABDOMEN STENT 960 B2 ABDOMEN MESH 960 B3 ABDOMEN CATHETER 960 C UE ALL OTHER 960 C1 UE ARM 960 C2 UE SHOULDER 960 C3 UE HAND 960 D LE ALL OTHER 960 D1 LE HIP 960 D2 LE KNEE 960 D3 LE FOOT 960 E THORACIC ALL OTHER 960 E1 THOR PACEMAKER/LEADS 960 E2 THOR ICD/LEADS 960 E3 THOR STENTS 960 E4 THOR VALVE 960 E5 THORACIC A/O 960 F DENTAL IMPLANTS 960 G ALL SCRWS, PLTS, ANCRS, ETC. 960 X SI UNKNOWNS (ALL)
MISC	999 A AL/OTH ITEMS 999 X HCPCS NOT GRP 999 Z NO HCPCS
Repair Activities	
WHEELCHAIRS AND ACCESSARIES	R10 NO LONGER USED R10 A WHEELCHAIR R10 B CARRIERS R10 C NSC VAN MODS
ARTIFICIAL LEGS	R20 A LEG A/K R20 B NO LONGER USED R20 C LEG B/K R20 D LEG ALL OTHER
ARTIFICIAL ARMS AND TERMINAL DEVICES	R30 ART ARM,TOTAL
ORTHOSIS	R40 ORTHOSIS TOTAL
SHOES/ORTHOTICS	R50 A ORTH SHOE ALL R50 B SHOE MOD R50 C A/O ITEM SERV
SENSORI-NEURO AIDS	R60 A AID FOR BLIND R60 B EYEGLASS RPR R60 C HEARING AID R60 D ASST LISTENING DEVICE R60 E SPEECH DEVICES

APPENDIX A (continued)

TABLE XXI: NPPD GROUPS AND NPPD[A] LINES USED BY THE VHA IN CODING ALL PROSTHETIC DEVICES PROVIDED BY THE PROSTHETICS SERVICE (DEPARTMENT OF VETERANS AFFAIRS, 2014) (CONTINUED)

NPPD Group	NPPD Line
HOME DIALYSIS EQUIPMENT	R70 HOME DIAL EQP
MEDICAL EQUIPMENT	R80 A PATIENT LIFTS R80 B REPAIR TO ECU R80 C MED EQUIP A/O R80 D HME DELIVERY/PICKUP R80 E TELEHEALTH R80 F COMPUTERS
ALL OTHER	R90 ALL OTHER R90 A NO LONGER USED R90 B TRAINING
OXYGEN & RESPIRATORY	R91 A CONCENTRATOR R91 B VENTILATOR R91 C EQUIPMENT A/O R91 D SERVICE VISIT R91 E COMPRESSED 02 R91 F LIQUID 02 (LBS.) R91 G LIQUID DEL SYS R91 H RESPIRATORY EQUIP
ADAPTIVE EQUIPMENT (*Not active)	*R92 A MOD VAN *R92 B ADAPT EQUIPMENT
MISC	R99 A SHIPPING R99 B NONRESPONSE R99 X HCPCS NOT GRP R99 Z NO HCPCS

[a] NPPD - The National Patient Prosthetics Database

APPENDIX A (continued)

TABLE XXII: CODES USED IN CHAPTER ONE FOR VARIABLES RELATED TO ASSISTIVE DEVICES AND HEALTH CONDITIONS AND WHICH WERE TESTED IN REGRESSION MODELS FOR DEVELOPMENT OF A MOBILITY LIMITATION ALGORITHM

Variable name	**Relevant codes (ICD9 or DME)**	**Data source**
Assistive device use		
receipt of power or manual wheelchair	Wheelchairs and accessories NPPD group	NPPD[a]
receipt of walker, cane, etc.	NPPD line 900A	NPPD
receipt of a prosthetics or orthotics	Artificial legs and or orthotics NPPD group	NPPD
Indicators of home modifications related to lack of mobility	Includes: hospital beds, patient lift, ECU, home safety equip. made this 900A-900F, 900H, 900I, 900K(except for walker/cane ones), 900L (adapted exercise equip), 910A, 940A, 940B, 960D1-D3, 999A, R80A-C (take out VA127), R90,R90A	NPPD
Surgical implants for hip, knee, and foot.	Surgical implants NPPD group	NPPD
Health Conditions		
Injuries, fractures related to mobility limitation	805.0-805.9; 806.00-806.9; 808.0-808.9; 905.0-905.9; 907.0-907.9; 928.0-928.9	ICD9 Diagnosis codes
Diseases of the musculoskeletal system and connective tissue	715; 717.0-717.9; 720.0-720.9; 721.0-721.91; 722.0-722.93 723.0-723.9; 724.0-724.9; 725; 728.0-728.9; 732.0-732.9	ICD9 Diagnosis codes
Diseases of the central nervous system	332.0; 333.0-333.99; 334.0-334.9; 337.00-337.9; 340; 341.0-341.9; 348.0-348.9; 349.0-349.9;	ICD9 Diagnosis codes
Difficulty walking or abnormal gait	781.2; 719.7	ICD9 Diagnosis codes
Joint replacements	ICD 9: 81.54, 81.55 OR CPT codes 27437–27447 ICD 9: 81.51, 81.53 OR CPT codes 27130.	ICD9 Diagnosis codes and CPT codes

APPENDIX A (continued)

TABLE XXII: CODES USED IN CHAPTER ONE FOR VARIABLES RELATED TO ASSISTIVE DEVICES AND HEALTH CONDITIONS AND WHICH WERE TESTED IN REGRESSION MODELS FOR DEVELOPMENT OF A MOBILITY LIMITATION ALGORITHM (CONTINUED)

Variable name	**Relevant codes (ICD9 or DME)**	**Data source**
Disorders of the peripheral nervous system	353.0-353.9; 355.0-355.9; 356.0-356.9; 357.0-357.9; 359.0-359.9	ICD9 Diagnosis codes
Paralytic related conditions	344.30, 344.31, 334.32; 438.40, 438.41, 438.42; 344.40, 344.41, 334.42; 438.30, 438.31, 438.32,342.00-342.92; 438.20, 438.21, 438.22; 344.00-344.1; 438.50, 438.51, 438.52, 438.53; 344.60 - 344.9	ICD9 Diagnosis codes
Morbid obesity	Based on BMI >40	CDW
amputation	84.10–84.19	ICD 9 procedure codes
sarcopenia	728.2	ICD9 Diagnosis codes
Stroke	430, 431,434, 436	ICD9 Diagnosis codes
Asthma	49300, 49301, 49302, 49310, 49311, 49312, 49320, 49321, 49322, 49381, 49382, 49390, 49391, 49392	ICD9 Diagnosis codes
COPD	490 , 4910 , 4911 , 49120 , 49121 , 49122 , 4918 , 4919 , 4920 , 4928 , 496	ICD9 Diagnosis codes
Hearth disease	('39891', '40201', '40211', '40291', '40401', '40403', '40411', '40413', '40491', '40493', '4293') or the first 3 digits of ICD9 in ('425', '428')	ICD9 Diagnosis codes

APPENDIX A (continued)

TABLE XXII: CODES USED IN CHAPTER ONE FOR VARIABLES RELATED TO ASSISTIVE DEVICES AND HEALTH CONDITIONS AND WHICH WERE TESTED IN REGRESSION MODELS FOR DEVELOPMENT OF A MOBILITY LIMITATION ALGORITHM (CONTINUED)

Variable name	**Relevant codes (ICD9 or DME)**	**Data source**
Cancer	179', '181', '185', '193') or ('140' <= substr(dx(k),1,3) <= '172') or substr(dx(k),1,3) in ('174', '175', '176', '180', '182', '183', '184', '194', '195') or ('186' <= substr(dx(k),1,3) <= '192') or ('200' <= substr(dx(k),1,3) <= '208') or upcase(dx(k)) in ('2303', '2304', '2312', '2330', '2332', '2334', '2386', '2730', '2733', 'V1005', 'V1006', 'V1011', 'V103', 'V1042', 'V1046') ; sx(j) = '605'; cpt_cd in ('54530', '54535', '55810', '55812', '55815', '55840', '55842', '55845', '55866'	ICD9 Diagnosis codes, procedure codes and CPT codes
Cerebrovascular disease (CVD)	dx(k) in ('36234', '430', '431', '436', '7814', '7843') or substr(dx(k),1,3) in ('432', '433', '434', '435', '437', '438') or substr(dx(k),1,4) = '9970'; sx(j) in ('3812', '3842', '3855', '3922', '3928', '3959');cpt_cd in ('33891', '35001', '35002', '35005', '35180', '35188', '35231', '35261', '35301', '35390', '35501', '35506', '35507', '35508', '35509', '35510', '35511', '35512', '35515', '35526', '35601', '35606', '35612', '35626', '35642', '35645', '35691', '35693', '35694', '35695', '35901', '61680', '61682', '61684', '61686', '61690', '61692')	ICD9 Diagnosis codes, procedure codes and CPT codes
Dementia	dx(k) in ('2940', '2948', '3310', '3312', '3317', '797') or substr(dx(k),1,3) = '290' or substr(dx(k),1,4) in ('2941', '3311')	ICD9 Diagnosis codes
Depression	dx(k) in ('29620' '29621''29622' '29623' '29624' '29625' '29626' '29630 '29631' '29632' '29633' '29634' '29635' '29636' '29650' '29651', '29652' '29653' '29654' '29655' '29656' '29660' '29661' '29662', '29663' '29664' '29665' '29666' '29689' '2980' '3004' '3091' '311')	ICD9 Diagnosis codes

APPENDIX A (continued)

TABLE XXII: CODES USED IN CHAPTER ONE FOR VARIABLES RELATED TO ASSISTIVE DEVICES AND HEALTH CONDITIONS AND WHICH WERE TESTED IN REGRESSION MODELS FOR DEVELOPMENT OF A MOBILITY LIMITATION ALGORITHM (CONTINUED)

Variable name	**Relevant codes (ICD9 or DME)**	**Data source**
Diabetes without complications	('2490' <= substr(dx(k),1,4) <= '2493') or ('2498' <= substr(dx(k),1,4) <= '2499') or ('2500' <= substr(dx(k),1,4) <= '2503') or ('2508' <= substr(dx(k),1,4) <= '2509')	ICD9 Diagnosis codes
Diabetes with complications	dx(k) in ('3572', '36201', '36202', '36203', '36204', '36205', '36206', '36641') or ('2494' <= substr(dx(k),1,4) <= '2497') or ('2504' <= substr(dx(k),1,4) <= '2507')	ICD9 Diagnosis codes
Liver disease	upcase(dx(k)) in ('0706', '0709', '07022', '07023', '07044', '4560', '4561', '5722', '5723', 5724', '5728', '5734', 'V427') or substr(dx(k),1,4) = '4562' sx(j) in ('391', '4291', '8864') cpt_cd in ('35636', '37140', '37145', '37160', '37180', '37181', '37182','37183', '43204', '43205', '43400', '43401', '75885', '75887')	ICD9 Diagnosis codes, procedure codes and CPT codes

APPENDIX A (continued)

TABLE XXII: CODES USED IN CHAPTER ONE FOR VARIABLES RELATED TO ASSISTIVE DEVICES AND HEALTH CONDITIONS AND WHICH WERE TESTED IN REGRESSION MODELS FOR DEVELOPMENT OF A MOBILITY LIMITATION ALGORITHM (CONTINUED)

Variable name	**Relevant codes (ICD9 or DME)**	**Data source**
peripheral vascular disease (PVD)	dx(k) in ('0930', '4373', '4431', '4439', '4471', '5571', '5579', '7854', 'V434') |substr(dx(k),1,3) in ('440', '441', '442') | ('4432' <= substr(dx(k),1,4) <= '4438') sx(j) in ('3813', '3814', '3815', '3816', '3818', '3833', '3834', '3836', '3838', '3843', '3844', '3846', '3848', '3956') or (('3923' <= sx(j) <= '3929') and sx(j) not in ('3927', '3928')) cpt_cd in ('33320', '33321', '33322', '33330', '33332', '33335', '33619','33764', '33803', '33840', '33845', '33851', '33860', '33861', '33863', '33864', '33870', '33875', '33877', '34510', '34520', '34530', '34813', '34830', '34831', '34832', '35011', '35013', '35045', '35081', '35082', '35091', '35092', '35102', '35103', '35111', '35112', '35121', '35122', '35131', '35132', '35141', '35142', '35151', '35152', '35182', '35184', '35189', '35190', '35211', '35216', '35236', '35241', '35246', '35251', '35256', '35266', '35271', '35276', '35281', '35286', '35302', '35303', '35304', '35305', '35306', '35311', '35321', '35331', '35341', '35351', '35355', '35361', '35363', '35371', '35372', '35381', '35516', '35518', '35521', '35522', '35523', '35525', '35531', '35533', '35535', '35536', '35537', '35538', '35539', '35540', '35541', '35546', '35548', '35549', '35551', '35556', '35558', '35560', '35563', '35565', '35566', '35570', '35571', '35582', '35583', '35585', '35587', '35616', '35621', '35623', '35631', '35632', '35633', '35634', '35637', '35638', '35641', '35646', '35647', '35650', '35651', '35654', '35656', '35661', '35663', '35665', '35666', '35671', '35681', '35682', '35683', '35686', '35879', '35903', '35907', '37788', '37790')	ICD9 Diagnosis codes, procedure codes and CPT codes

APPENDIX A (continued)

TABLE XXII: CODES USED IN CHAPTER ONE FOR VARIABLES RELATED TO ASSISTIVE DEVICES AND HEALTH CONDITIONS AND WHICH WERE TESTED IN REGRESSION MODELS FOR DEVELOPMENT OF A MOBILITY LIMITATION ALGORITHM (CONTINUED)

Variable name	**Relevant codes (ICD9 or DME)**	**Data source**
Substance abuse	dx(k) in ('291' '2910' '2911' '2912' '2913' '2914' '2915' '2919' '3030' '30303' '3039' '30390' '30391' '30392' '30393' '303x' '30300' '30301' '30302' '30303' '30390' '30391' '30392' '30393' '3050' '30500' '30501' '30502' '30503' '3575' '4255' '53530' '53531' '5710' '5711' '5712' '5713' '7903' 'V6542' 'V113') sx(j) in ('9445' '9446' '9453' '9454' '946' '9461' '9462' '9463' '9464' '9465' '9466' '9467' '9468' '9469') cpt_cd in ('99408' '99409' '4320F' 'H0005' 'H0006' 'H0007' 'H0008' 'H0009' 'H0010' 'H0011' 'H0012' 'H0013' 'H0014' 'H0015' 'H0020' 'H0050' 'H0034' 'G0396' 'G0397' 'H0047' 'H2035' 'H2036' 'S9475' 'H2034' 'T1006' 'T1007' 'T1008' 'T1009' 'T1010' 'T1011' 'T1012')	ICD9 Diagnosis codes, procedure codes and CPT codes
Renal disease	upcase(dx(k)) in ('0954', '2230', '23691', '2714', '27410', '28311', '40301', '40311', '40391', '40402', '40403', '40412', '40413', '40492', '40493', '5830', '5831', '5832', '5833', 5834', '5835', '5836', '5837', '586', '587', '591', '75319', '7944', 'V420') or ('75312' <= dx(k)<= '75317') or upcase(substr(dx(k),1,3)) in ('580', '581', '582', '584', '585', '588', 'V56') or upcase(substr(dx(k),1,4)) in ('0160', '7532', 'V451') sx(j) in ('3927', '3942', '5498') or ('3993' <= sx(j) <= '3995') cpt_cd in ('36147', '36148', '36248', '36500', '36800', '36810', '36815', '36818', '36819', '36820', '36821', '36825', '36830', '36832', '36833', '36835', '37607', '49324', '49325', '49420', '49421', '49435', '49436', '90935', '90937', '90945', '90947', '90997','90999')	ICD9 Diagnosis codes, procedure codes and CPT codes

[a] NPPD - The National Patient Prosthetics Database

APPENDIX A (continued)

TABLE XXIII: REGRESSION MODELS TESTED IN CHAPTER ONE FOR BINARY MILD TO SEVERE MOBILITY LIMITATION OUTCOME WITH A 1-YEAR TIME WINDOW USING HEALTHCARE ADMINISTRATIVE DATA AMONG VETERANS IN THE WAVES STUDY WHO COMPLETED THE MEDICARE CURRENT BENEFICIARY SURVEY, 2010-2013[a]

	Coefficient	Std. Err.	z	P>z	[95% Confidence	Interval]
Census Division West South Central	0.787117	0.248099	3.17	0.002	0.300852	1.273383
Chronic obstructive pulmonary disease	2.533882	0.828086	3.06	0.002	0.910863	4.156901
VHA copayment group 1	0.684505	0.135691	5.04	0.000	0.418556	0.950454
Prosthetics or orthotics	1.237647	0.383097	3.23	0.001	0.486792	1.988502
Wheelchairs (manual and electric)	3.713326	0.539641	6.88	0.000	2.65565	4.771001
Peripheral vascular disease	0.833796	0.383403	2.17	0.03	0.082341	1.585251
BMI	0.083293	0.013673	6.09	0.000	0.056495	0.110091
Diseases of the musculoskeletal system and connective tissue	0.794801	0.167685	4.74	0.000	0.466145	1.123458
Diseases of the central nervous system	1.661647	0.418839	3.97	0.000	0.840737	2.482557
Constant	-3.34235	0.422564	-7.91	0.000	-4.17056	-2.51414

[a] Regressors kept based on logistic regression with backwards selection.

APPENDIX A (continued)

TABLE XXIV: REGRESSION MODELS TESTED IN CHAPTER ONE FOR BINARY MILD TO SEVERE MOBILITY LIMITATION OUTCOME WITH ONLY GENERALIZABLE PREDICTORS USING HEALTHCARE ADMINISTRATIVE DATA AMONG VETERANS IN THE WAVES STUDY WHO COMPLETED THE MEDICARE CURRENT BENEFICIARY SURVEY, 2010-2013[a]

	Coefficient	Std. Err.	z	P>z	[95% Conf.	Interval]
Age category (reference age<65)						
Ages 65-74	-1.08018	0.205721	-5.25	0.000	-1.48339	-0.67698
Ages 75+	-0.81846	0.278752	-2.94	0.003	-1.3648	-0.27212
Home modifications	3.251268	0.528678	6.15	0.000	2.215078	4.287457
Prosthetics or orthotics	1.4791	0.337317	4.38	0.000	0.81797	2.140229
Wheelchairs (manual and electric)	1.86831	0.558759	3.34	0.001	0.773162	2.963457
Peripheral vascular disease	0.793177	0.340547	2.33	0.02	0.125719	1.460636
Diseases of the musculoskeletal system and connective tissue	0.58617	0.189699	3.09	0.002	0.214366	0.957973
Depression	0.530979	0.202492	2.62	0.009	0.134102	0.927857
Diseases of the central nervous system	1.190901	0.381996	3.12	0.002	0.442203	1.939599
Chronic obstructive pulmonary disease	2.328234	0.751896	3.1	0.002	0.854546	3.801922
Diabetes without complications	0.425493	0.16842	2.53	0.012	0.095397	0.755589
Diabetes with complications	0.755608	0.365558	2.07	0.039	0.039128	1.472087
Census Division West South Central	0.897877	0.280334	3.2	0.001	0.348433	1.447322
Difficulty walking or abnormal gait	1.194206	0.488035	2.45	0.014	0.237675	2.150737
Constant	-0.41774	0.208097	-2.01	0.045	-0.82561	-0.00988

[a] Regressors kept based on logistic regression with backwards selection

APPENDIX A (continued)

TABLE XXV: CUT-OFFS FOR MAXIMIZING SENSITIVITY AND SPECIFICITY BASED OFF THE BINARY MILD-TO-SEVERE AND MODERATE-TO-SEVERE MOBILITY LIMITATION APPROACHES TESTED IN CHAPTER ONE

Version	Cut-off based on Youden's Index[a]
Binary mild-to-severe mobility limitation version	0.440
Binary moderate-to-severe mobility limitation version	0.289

[a]Youden's Index is the point on the Receiver Operator Curve that maximizes sensitivity and specificity (Youden, 1950)

APPENDIX B

<u>Comparison of Medicare and Non-Medicare enrollee characteristics with those in the MCBS.</u>

Table XXVI compares the sample used in chapter one to develop a predictive algorithm with the full WAVES sample stratified by those who were enrolled and those who were not enrolled. This comparison was done to examine how different the full WAVES sample was from the sample used in chapter one, which was considerably smaller (n=964) and was a convenience sample and did not represent the characteristics of the whole MCBS sample or Veterans who use the VHA. In this analysis, there was only ;838 veterans from MCBS who merged to the analytic dataset used in Chapter 2 as additional exclusions were done in Chapter 2.

Compared to those in the full WAVES sample enrolled in Medicare in 2010, the MCBS sample was more likely to have a mobility limitation, included a larger percentage of younger age groups as well as older age groups, and had a lower percentage of veterans who had no comorbidities from the Quan comorbidity index. However, the MCBS sample differed more compared to those who were not enrolled in Medicare in 2010.

Compared to the not enrolled in Medicare group, the MCBS sample had a lower BMI, had a higher percentage with a mobility limitation, and had more people who were normal weight or overweight, but less people who were obese. The MCBS sample was also older compared to those not enrolled in Medicare, which makes sense given the requirements of Medicare. The MCBS sample was less likely to be separate/divorced, or widowed, had higher comorbidity scores, were more likely to have substance abuse disorder, sarcopenia, and stroke, and had more hospital admissions and longer lengths of stay.

APPENDIX B (continued)

TABLE XXVI: COMPARISON OF BASELINE CHARACTERISTICS BETWEEN VETERANS IN THE MCBS SAMPLE WITH VETERANS ENROLLED IN MEDICARE IN 2010 AS WELL AS THOSE NOT ENROLLED IN MEDICARE IN 2010 [ab]

	MCBS	**Enrolled in Medicare in 2010**	**p-value**	**MCBS**	**Not enrolled in Medicare in 2010**	**p-value**
N	838	778,376		838	875,166	
Body Mass Index (*M and SD*)	29.5 (5.8)	29.8 (5.9)	0.26	29.5 (5.8)	30.8 (6.0)	**<0.001**
Mobility limitation[c]	49.3	41.1	**<0.001**	49.3	30.07	**<0.001**
Underweight	1.0	0.9	0.885	1.0	0.63	0.228
Normal weight	19.2	18.3	0.519	19.2	14.14	**<0.001**
Over weight	38.9	38.5	0.795	38.9	35.10	**0.021**
Class-1 obese	25.7	26.2	0.703	25.7	29.67	**0.011**
Class-2 obese	9.1	10.6	0.156	9.1	13.29	**<0.001**
Class-3 obese	6.2	5.5	0.345	6.2	7.18	0.275
Age 20-39	2.5	0.9	**<0.001**	2.5	2.35	0.770
Age 40-49	3.8	2.4	**0.005**	3.8	3.97	0.818
Age 50-64	13.7	21.5	**<0.001**	13.7	92.79	**<0.001**
Age 65-74	37.7	44.3	**<0.001**	37.7	0.75	**<0.001**
Age 75+	42.2	31.0	**<0.001**	42.2	0.13	**<0.001**
Unknown marital status	0.4	0.4	0.997	0.4	0.59	0.373
Married	64.6	63.6	0.547	64.6	63.70	0.605
Separated/divorced	18.1	20.7	0.069	18.1	22.62	**0.002**
Widowed	7.8	6.7	0.223	7.8	2.75	**<0.001**
Single	9.2	8.7	0.612	9.2	10.34	0.275
Non-Hispanic White	72.8	73.4	0.677	72.8	71.44	0.385
Non-Hispanic Black	12.1	11.9	0.906	12.1	15.26	**0.010**
Hispanic	3.2	3.0	0.701	3.2	3.21	0.980
Other	2.3	1.7	0.192	2.3	1.86	0.389

APPENDIX B (continued)

TABLE XXVI: COMPARISON OF BASELINE CHARACTERISTICS BETWEEN VETERANS IN THE MCBS SAMPLE WITH VETERANS ENROLLED IN MEDICARE IN 2010 AS WELL AS THOSE NOT ENROLLED IN MEDICARE IN 2010 [ab] (CONTINUED)

	MCBS	**Enrolled in Medicare in 2010**	**p-value**	**MCBS**	**Not enrolled in Medicare in 2010**	**p-value**
Unknown	9.7	10.0	0.769	9.7	8.23	0.130
No comorbidity	35.8	40.3	**0.008**	35.8	59.08	**<0.001**
Comorbidity score of 1-3	51.4	48.6	0.107	51.4	37.72	**<0.001**
Greater than 4 comorbidity score	12.8	11.0	0.109	12.8	3.20	**<0.001**
Quan Comorbidity score (*M and SD*)	1.0 (0.0, 2.0)	1.0 (0.0, 2.0)	**0.011**	1.0 (0.0, 2.0)	0.0 (0.0, 1.0)	**<0.001**
Depression	24.5	23.0	0.309	24.5	27.07	0.089
Substance abuse disorder	9.2	10.0	0.409	9.2	13.86	**<0.001**
Sarcopenia	0.4	0.4	0.963	0.4	0.05	**<0.001**
Stroke	6.8	5.3	0.052	6.8	2.24	**<0.001**
Metro	73.0	74.9	0.209	73.0	73.53	0.746
Hospital admissions (*M and SD*)	0 (0, 0)	0 (0, 0)	0.067	0 (0, 0)	0 (0, 0)	**0.039**
Length of stay (*M and SD*)	0 (0, 0)	0 (0, 0)	0.063	0 (0, 0)	0 (0, 0)	**0.038**
# of primary care encounters (*M and SD*)	2 (1, 4)	2 (1, 4)	0.034	2 (1, 4)	3 (2, 4)	<0.001

[a] Statistical comparisons made Using Z-test of proportions for all except for continuous variables that used Wilcoxon rank-sum test.

[b] Statistically significant differences were bolded.

[c] Mobility limitation is a predicted binary variable derived from a model in chapter one. The variable is lagged one-year.

APPENDIX B (continued)

Additional analysis of a Quantile regression of mobility limitation across the BMI distribution

It is possible that the effect of mobility limitation on BMI varies across the distribution of BMI. In other words, the effect of mobility limitation may have a stronger association at the upper end of the BMI distribution than the lower end. There has been no previous research that has examined the effect of mobility limitation across the distribution of BMI. I used a series of cross-sectional quantile regressions to estimate the effect of mobility limitation at quantiles of 10^{th} , 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles of the BMI distribution. Below is the equation for the quantile regression used:

$$(7)\ BMI_{it} = \beta_0^{(p)} + \beta_1^{(p)} moblim_{it} + \beta_2^{(p)} X_{it} + \beta_3^{(p)} T_t + \varepsilon_{it}$$

where 0<p<1 is the proportion of the sample having scores below the quantile at p. As described by Hao, Naiman, and Naiman (2007) on page 29, "The conditional pth quantile is determined by the quantile specific parameters and specific values of X_i" at the quantiles 0.10, 0.25,0.50, 0.75, and 0.90. *BMI* is the outcome for the individual i in time period t. β_0 is the year specific intercept; $\beta_1 moblim_{it}$ is the binary mobility limitation variable, $\beta_2 X_{it}$ is a vector of the covariates: Quan group, year, age group, substance abuse disorder, depression, sarcopenia, stroke, metro, marital status, hospital admission, length of stay, primary care encounters, specialist care encounters, and dying or dead in that year, $\beta_3 T_t$ is the year fixed effects, which capture secular trends, and ε_{it} is the error term.

Results of Quantile regression:

In Table XXVII, I show the results of the cross-sectional quantile regression used to examine how the effect of mobility limitation on BMI might vary across the distribution of BMI. The effect of mobility limitation on BMI at the lower tail of the BMI distribution (10^{th} percentile) is only 0.48 BMI units

APPENDIX B (continued)

(p<0.001) for males and 0.63 BMI units (p<0.001) for females. The effect of BMI increases at 25th percentile, 50th percentile and 75th percentile. At the 90th percentile, the effect of mobility limitation is the largest at 1.72 BMI units (p<0.001) for males and 1.46 BMI units (p<0.001) for females.

TABLE XXVII: ASSOCIATIONS BETWEEN MOBILITY LIMITATION AND QUANTILES OF THE BMI DISTRIBUTION BASED ON CROSS-SECTIONAL QUANTILE REGRESSIONS USING THE WEIGHT AND VETERANS ENVIRONMENTS STUDY, 2009-2015

	Males		**Females**	
Quantiles	**Mobility limitation**	**SE**	**Mobility limitation**	**SE**
10%	0.481***	(0.005)	0.632***	(0.019)
25%	0.720***	(0.003)	0.997***	(0.019)
50%	1.028***	(0.004)	1.224***	(0.020)
75%	1.391***	(0.005)	1.364***	(0.025)
90%	1.725***	(0.008)	1.461***	(0.036)

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

[a] Coefficients are reported from quantile regressions controlling for the following covariates: Quan comorbidity group, year fixed effects, age group, substance abuse disorder, depression, sarcopenia, stroke, metro, marital status, hospital admission, length of stay, primary care encounters, specialist care encounters, and dying or dead in that year.

[b] Mobility limitation is a predicted binary variable derived from a model in chapter one. The variable is lagged one-year.

Discussion of quantile regression results

These results suggest that the association with body weight is largest at the upper tail of the BMI distribution at the 75th and 90th quantiles. There is still a positive association at the lower tail of the BMI distribution, but it is smaller. Future work could be done to analyze how mobility limitation affects BMI across the BMI distribution using a longitudinal analysis with individual-level fixed effects. Based on the work by Forman-Hoffman et al. (2008) who showed that people who gained mobility limitations were

APPENDIX B (continued)

more likely to both gain and lose 5% weight, a longitudinal analysis might show an association between both increase and decrease in BMI. It would be interest to know if one had a stronger association. Based on this dissertation, it would also be of interest to know how the association of mobility limitations differs across the BM distribution differently for certain groups such as older adults. Future work is warranted in this area.

APPENDIX B (continued)

TABLE XXVIII: RESULTS FROM REGRESSION MODELS OF BMI REGRESSED ON MOBILITY LIMITATION WITH INTERACTIONS WITH AGE AND QUAN COMORBIDITY GROUPS FOR VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY 2009-2015 [a,b]

	Males N =13,381,684			Females N= 989,516		
	Original Fixed-Effects Model	Age X Mobility limitation interaction	Quan Comorbidity Group X Mobility limitation interaction	Original Fixed-Effects Model	Age X Mobility limitation interaction	Quan Comorbidity Group X Mobility limitation interaction
Mobility limitation[c]	0.0428***	0.662***	0.131***	0.104***	0.533***	0.194***
	(0.00241)	(0.00943)	(0.00326)	(0.0108)	(0.0198)	(0.0123)
Mobility limitation X age group (ref ages 20-39 & no mobility limitation)						
Mobility limitation X age group 40-49		-0.286***			-0.280***	
		(0.0111)			(0.0245)	
Mobility limitation X age group 50-64		-0.503***			-0.614***	
		(0.00996)			(0.0237)	
Mobility limitation X age group 65-74		-0.714***			-0.903***	
		(0.00990)			(0.0318)	
Mobility limitation X age group 75-86		-0.962***			-1.172***	
		(0.0102)			(0.0426)	
Mobility limitation X Quan comorbidity group (ref no comorbidity group & no mobility limitation)						
Mobility limitation X Quan comorbidity group score 1-3			-0.140***			-0.284***
			(0.00397)			(0.0195)
Mobility limitation X Quan comorbidity group score >=4			-0.259***			-0.404***
			(0.00824)			(0.0684)

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

APPENDIX B (continued)

TABLE XXVIII: RESULTS FROM REGRESSION MODELS OF BMI REGRESSED ON MOBILITY LIMITATION WITH INTERACTIONS WITH AGE AND QUAN COMORBIDITY GROUPS FOR VETERANS IN THE WEIGHT AND VETERANS ENVIRONMENT STUDY 2009-2015 [a,b] (CONTINUED)

	Males N =13,381,684			Females N= 989,516		
	Original Fixed-Effects Model	Age X Mobility limitation interaction	Quan Comorbidity Group X Mobility limitation interaction	Original Fixed-Effects Model	Age X Mobility limitation interaction	Quan Comorbidity Group X Mobility limitation interaction

[a] Coefficients are reported from linear regressions controlling for the following covariates: Quan comorbidity group, year fixed effects, age group, substance abuse disorder, depression, sarcopenia, stroke, metro, marital status, hospital admission, length of stay, primary care encounters, specialist care encounters, and dying or dead in that year.

[b] Standard errors reported in parenthesis.

[c] Mobility limitation is a predicted binary variable derived from a model in chapter one. The variable is lagged one-year.

APPENDIX C

UNIVERSITY OF ILLINOIS
AT CHICAGO

Office for the Protection of Research Subjects (OPRS)
Office of the Vice Chancellor for Research (MC 672)
203 Administrative Office Building
1737 West Polk Street
Chicago, Illinois 60612-7227

Approval Notice
Amendment to Research Protocol and/or Consent Document – Expedited Review
UIC Amendment # 12

August 11, 2017

Shannon Zenk, Ph.D.
Health Systems Science
845 S Damen Avenue
914 NURS, M/C 802
Chicago, IL 60612
Phone: (312) 355-2790 / Fax: (312) 996-7725

RE: Protocol # 2013-0650
"Environmental Attributes and Veterans' Weight Control"

Dear Dr. Zenk:

Members of Institutional Review Board (IRB) #3 have reviewed this amendment to your research and/or consent form under expedited procedures for minor changes to previously approved research allowed by Federal regulations [45 CFR 46.110(b)(2) and/or 21 CFR 56.110(b)(2)]. The amendment to your research was determined to be acceptable and may now be implemented.

Please note the following information about your approved amendment:

Amendment Approval Date: August 11, 2017
Amendment:
Summary: UIC Amendment #12 received on July 31, 2017 is an investigator-initiated change in key research personnel to remove research personnel: Anita Bontu, Haytham Abu Zayd and to add research personnel: Yochai Eisenberg
Approved Subject Enrollment #: 4000000
Performance Sites: UIC, Hines VA
Sponsor: NIH/NCI

Please note the Review History of this submission:

Receipt Date	Submission Type	Review Process	Review Date	Review Action
07/31/2017	Amendment	Expedited	08/11/2017	Approved

APPENDIX C (continued)

Please be sure to:

→ Use your research protocol number (2013-0650) on any documents or correspondence with the IRB concerning your research protocol.

→ Review and comply with all requirements on the guidance, **"UIC Investigator Responsibilities, Protection of Human Research Subjects"** (*http://tigger.uic.edu/depts/ovcr/research/protocolreview/irb/policies/0924.pdf*)

Please note that the UIC IRB #3 has the right to ask further questions, seek additional information, or monitor the conduct of your research and the consent process.

Please be aware that if the scope of work in the grant/project changes, the protocol must be amended and approved by the UIC IRB before the initiation of the change.

We wish you the best as you conduct your research. If you have any questions or need further help, please contact the OPRS at (312) 996-1711 or me at (312) 413-3788. Please send any correspondence about this protocol to OPRS at 203 AOB, M/C 672.

Sincerely,

Rachel Olech, B.A., CIP
Assistant Director, IRB # 3
Office for the Protection of Research Subjects

Enclosure(s): None

cc: Lorna K. Finnegan, Health Systems Science, M/C 802

APPENDIX D

From: permissions@who.int
To: Eisenberg, Yochai
Cc: permissions@who.int
Subject: ID: 288357 Permission authorization for WHO copyrighted material **Date:** Thursday, May 16, 2019 10:16:13 AM

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Bachelor of Arts B.A., University of Wisconsin – Madison, (2005)

PROFESSIONAL EXPERIENCE

August 2008 – present; Senior Research Specialist (Project Coordinator 2008-2017); UIC Center on Health Promotion Research for Persons with Disabilities, Department of Disability and Human Development

Specific roles and responsibilities in individual projects (*by project title*) include:

- <u>Principal Investigator</u> – *Neighborhood Environment Moderation of Disability and Obesity Association*. Conducting secondary analysis of healthcare administrative data linked to GIS data as part of my dissertation work.
- <u>Co-Principal Investigator</u> **-** *Development of a Mobility Disability Algorithm.* Leading efforts and conducting the data analysis to develop a mobility disability algorithm using electronic healthcare data.
- <u>Evaluation Lead</u> – *National Center on Health Physical Activity and Disability (NCHPAD)*. Lead evaluation of national center activities, which focus on development of a knowledge-to-action model for implementing policy, systems, and environmental changes and increasing participation of people with disabilities in health promotion.
- <u>Research Analyst</u> – *Idaho Department of Family Services*. Assisted with design, implementation, and analysis for an evaluation of Idaho's Non-Emergency Medical Transportation (NEMT) program.
- <u>Evaluation Consultant</u> – *National Association of Chronic Disease Directors (NACDD)*. Lead evaluation of Disability and Health Communities project, which set out to implement inclusive policy, systems, and environmental changes in 10 pilot communities.
- <u>Researcher and Statistical Support</u> – *Great Lakes ADA Center*. Conduct research on ADA transition plans through a systematic review, focus groups, interviews, and GIS analysis. Provide statistical support to other research projects at the Great Lakes ADA Center.
- <u>GIS analyst</u> – *Illinois WIC evaluation*. Analyze geographic factors such as accessibility that contribute to retention of women in WIC programs.
- <u>Transportation Consultant</u> – *Design for Disability: Access to Health and Transportation & Birmingham Transportation Health Impact Assessment*. Provided advice and feedback for a community design charrette about transportation for people with disabilities. Facilitated groups at a stakeholder charrette. Developed maps on demographics and transportation for people with disabilities in Birmingham, AL.
- <u>Principal Investigator</u> – *Development of a Community Health Inclusion Index (CHII).* Managed CDC study to develop an index for communities to measure how accessible their healthy living resources are, as a tool for prioritizing improvements. Facilitated focus groups and convened expert panels to develop content validity. Trained community

raters and led large scale field testing of the CHII in 5 states.

- Research Analyst **-** *An Independent Evaluation of Illinois Integrated Care Program.* Evaluated access to health care and transportation services as part of an evaluation of an Illinois pilot Integrated Care Program. Conducted qualitative interviews of Managed Care Organizations and data analysis of various health services.
- Co-Investigator – (1) *Micro-processor controlled Knee-Ankle-Foot Orthosis (C-Brace) vs. Stance-control Knee-Ankle-Foot Orthosis (SCO): Functional Outcomes in Individuals with Lower Extremity Impairments due to Neurological Disease &* (2) *Microprocessor Knee vs. Mechanical Knee: Impact on Functional Outcomes in Dysvascular Transfemoral Amputees*. Assessed the level of community participation and neighborhood travel patterns of people with amputations pre and post being given a microprocessor knee and foot (2 separate studies) by analyzing data collected through GPS data loggers. Co-authored paper in the *Physical Therapy Journal*.

August 2010- Present; Adjunct Lecturer; Department of Urban Planning and Policy at the University of Illinois at Chicago;

- Instructed graduate students from urban planning and other related disciplines in courses on Geographic Information Systems (GIS) and its applications to analyze and visualize spatial data.
- Co-Developed and taught “Web Mapping Applications”; a class that introduced students to developing online interactive web maps and web mapping applications. (Summer 2017, and summer 2018)
- Taught “Intermediate GIS” (Fall 2013 – Spring 2017). In this course, students learn advanced techniques for creating and analyzing spatial data. Students become proficient at spatial data analysis and visualization through technical exercises and projects.
- Developed and taught “GIS Project Management Studio”; a class where students applied GIS skills to real world projects for an external client. (Summer 2014,2015,2016)
- Co-Taught “Intro to GIS for planners” (fall 2010 – spring 2013). Students learn the basics of GIS. Through guided exercises and homework, students become comfortable in using this new technical skill.

PEER-REVIEWED PUBLICATIONS

Eisenberg, Y., Grossman, B., (2018) Public Transportation. In Heller, T., Gill, C. J., Harris, S. P., & Gould, R. (Ed.). Disability in American Life: An Encyclopedia of Concepts, Policies, and Controversies (Vol2, pp 551-556) ABC-CLIO, LLC.

Vanderbom, K. A., **Eisenberg, Y**., Tubbs, A. H., Washington, T., Martínez, A. X., & Rauworth, A. (2018). Changing the Paradigm in Public Health and Disability through a Knowledge Translation Center. *International journal of environmental research and public health*, *15*(2), 328. doi:10.3390/ijerph15020328

Eisenberg, Y., Bouldin, E.D., Gell, N., Rosenberg D. (2017), Planning Walking Environments for People with Disabilities and Older Adults, in Corinne Mulley , Klaus Gebel , Ding (ed.) Walking (Transport and Sustainability, Volume 9) Emerald Publishing Limited, pp.187 - 209

Eisenberg Y., Vanderbom, K.A., & Vasudevan, V. (2017). Does the built environment moderate the relationship between having a disability and lower levels of physical activity? A systematic review. *Preventive Medicine*, 95s:S75-s84.

Nasseh, K., **Eisenberg Y**., & Vujicic, M. (2017). Geographic Access to Dental Care Varies in Missouri and Wisconsin. *Journal of Public Health Dentistry*, 77(3), 197-206.

Eisenberg Y., Rimmer, J.H., Mehta, T., & Fox, M.H. (2015). Development of a community health inclusion index: an evaluation tool for improving inclusion of people with disabilities in community health initiatives. *BMC Public Health Journal*, 15 (1):1050.

Owen, R., Bonardi, A., Bradley, V., Butterworth, J., Caldwell, J., Cooper, R., **Eisenberg, Y.**, Ford, M., Hewitt, A., Larson, S.A. and Rizzolo, M.K.,(2015) Long-term services and supports. *Inclusion*, 3(4), pp.233-241.

Jayaraman A., Deeny, S., **Eisenberg Y**., Mathur, R. & Kuiken, T. (2013). Global Position Sensing and Step Activity as Outcome Measures of Community Mobility and Social Interaction for an Individual With a Transfemoral Amputation Due to Dysvascular Disease. *Physical Therapy Journal*, 94, 401-410.

Rimmer, J., Wang, E. , **Eisenberg, Y**., Vasudevan V. (April 2010) Longitudinal perspective of secondary conditions and community accessibility in a predominantly African American group of women with mobility *Disability and Health Journal*, v3, 2, e6

MANUSCRIPTS IN PROCESS

Eisenberg, Y., Hieder, A. Gould, R. Jones, R. (in process) Findings from a systematic review of US Public Rights-of-way American with Disabilities Act (ADA) Transition Plans. Being submitted to the *Journal of Urban Planning and Development*.

Eisenberg, Y., Vanderbom, K.A., Harris, K., Hefelfinger, J., Rauworth, A., Griffin-Blake, S.,(in process) Implementation of the Disability and Healthy Community project: An inclusive public health initiative to impact the health and wellness of individuals with disability. Being submitted to *Preventive Medicine Reports*.

Eisenberg, Y., Crabb, C., Morales, M., Owen, R.,(in process) Having an independent rideshare driver for NEMT is not associated with ride satisfaction, but is associated with late and missed pickups. Being submitted to *Journal of Transport Geography*.

DISSERTATION

Topic: Mobility limitation, obesity and the neighborhood environment

Three papers

1. Development of a predictive algorithm for identifying veterans with mobility limitation using electronic healthcare records.
2. The effect of mobility limitation on weight change over time
3. Does the neighborhood environment moderate the relationship between mobility limitation & weight gain?

Committee:

- Dr. Lisa Powell, Distinguished Professor and Department Head, Dept. of Health Policy and Administration
- Dr. Shannon Zenk, Department of Health Systems Sciences
- Dr. Elizabeth Tarlov, Department of Health Systems Sciences
- Dr. Kiyoshi Yamaki, Department of Disability and Human Development
- Dr. Zeynep Isgor, Department of Health Policy and Administration

I received approval to use the data sets that Drs Zenk and Tarlov developed as part of an NIH RO1.

PEER-REVIEWED PRESENTATIONS

Eisenberg, Y., Tarlov, E., (Fall 2018), ‘Development and Validation of a Mobility Limitation Algorithm using Healthcare Administrative Data’. Poster, APHA Annual Conference, San Diego, CA

Eisenberg, Y., Bonner, K., Mungo, S., Riley, A., (Fall 2018), ‘Integrating disability inclusion into an evidence-based physical activity program at the national level to have impact on girls with disability locally’. Oral Presentation, APHA Annual Conference, San Diego, CA.

Eisenberg, Y., Lyons, S., (Fall 2017), 'Incorporating Disability into Community Health Assessments (CHAs) and Community Health Improvement Plans (CHIPs)'. Oral Presentation, APHA Annual Conference, Atlanta, GA.

Eisenberg, Y., Yamaki, K., Maass, A., (Fall 2017), 'Characteristics of organizations who are ready to make policy, systems and environmental changes towards inclusion'. Poster, APHA Annual Conference, Atlanta, GA.

Eisenberg, Y., Vanderbom, K.A., (Spring 2017), 'Community Health Inclusion Index (CHII) & Guidelines Recommendations and Adaptations Including Disability (GRAIDs)'. Workshop. Active Living Research Conference, Clearwater, FL.

Eisenberg, Y., Wilburn, K., Maass, A., (Spring 2017), 'Gathering local data on participation of people with disabilities in health promotion to further local community health planning'. Poster, Active Living Research Conference, Clearwater, FL.

Eisenberg, Y., Vanderbom, K.A., (Winter 2016), 'Using the Community Health Inclusion Index (CHII) & Guidelines Recommendations and Adaptations Including Disability (GRAIDs)'. Oral Presentation. AUCD, Washington D.C.

Eisenberg, Y., (Fall 2016), 'A spatial clustering analysis of disability prevalence and the influence of poverty, age and land use'. Round table, APHA Annual Conference, Denver, CO

Eisenberg, Y., Vanderbom, K.A., Edwards, K., Hefelfinger, J., Rauworth, A., (Fall 2016), 'Reaching People with Disabilities through Inclusive Healthy Communities: Results from Assessments of Community Health Inclusion'. Oral Presentation, APHA Annual Conference, Denver, CO

Eisenberg, Y., Vanderbom, K.A., Vasudevan V. , (Fall 2016), 'Including people With and Without disabilities in studies can help to better understand the relationship of the built environment, physical activity and disability; A systematic review'. Poster, APHA Annual Conference, Denver, CO

Eisenberg, Y., Mitchel, D., Yamaki, K. Wing, C., Heller, T., Owen, R., (Fall 2015), 'Assessing the Impact of a Transition to Managed Care on Non-Emergency Transportation Services'. Oral Presentation, APHA Annual Conference, Chicago, IL.

Eisenberg, Y., Vasudevan V. Rimmer, J., (Fall 2015), 'Validation of Built Environment Constructs on the Community Health Inclusion Index'. Oral Presentation, APHA Annual Conference, Chicago, IL.

Eisenberg, Y., Vasudevan V., (Fall 2014), Development of a Community Health Inclusion Index (CHII) for Measuring Accessibility and Inclusion of Physical Activity and Food Environments'. Oral Presentation, APHA Annual Conference, New Orleans, LA.

Eisenberg, Y., Vasudevan V., (Fall 2013), 'Environmental & social factors impacting transportation use among persons with disabilities'. Poster, APHA Annual Conference, Boston, MA

Eisenberg, Y., Vasudevan V. Rimmer J., (Fall 2011), 'An objective time use study of people with mobility disabilities using GPS trackers'. Poster, APHA Annual Conference, Washington D.C

Eisenberg, Y., Vasudevan V. Rimmer J., Wang, E. (Fall 2010) 'Assessing the need for a neighborhood rollability index for people who use wheelchairs using geographical information systems' Oral Presentation, *APHA Annual Conference,* Denver CO.

Eisenberg, Y., Vasudevan V., Rimmer J., Wang, E. (Fall 2009) 'Using GIS to explore access to physical activity supporting spaces (A-PASS) for people with mobility limitations' Poster, *APHA Annual Conference,* Philadelphia, PA

INVITED PRESENTATIONS/T.V. SHOW

Eisenberg, Y. (March 2017), 'Healthy Communities: An Assessment and Implementation Framework to Achieve Inclusion of Persons with Disability'. *Public Health Live (TV show).* University of Albany, School of Public Health. URL: https://www.albany.edu/sph/cphce/phl_0317.shtml

CURRENT FUNDING

University of Alabama Birmingham (Rimmer) 4/1/16 – 3/31/21

Centers for Disease Control and Prevention (CDC), National Center on Birth Defects and Developmental Disabilities (NCBDDD), Disability and Health Branch
National Center on Health Physical Activity and Disability (NCHPAD)
The purpose of this sub-award is to be the lead evaluator of the center, to train communities across the country on using the Community Health Inclusion Index, and providing technical assistance to communities.
Role: Lead Evaluator
Sub-award amount: $375,000

90DP0091-01-00 (Jones) 10/1/16 – 9/30/21
National Institute on Disability, Independent Living, and Rehabilitation Research
ADA National Network Regional Centers - Region V (Great Lakes ADA Center)
The purpose of the research is to enhance and complement technical assistance provided by the regional centers. I lead a study on the implementation of ADA transition plans in the U.S.
Role: Co-Investigator

COMPLETED RESEARCH SUPPORT
Center for Research on Health and Aging (Eisenberg) 11/1/17 – 10/31/18
National Institute on Aging, Roybal Center Dissertation Grant
Neighborhood Environment Moderation of Disability & Obesity Association.
The purpose of this dissertation award is to examine whether the neighborhood environment moderates the association between having a mobility disability and higher levels of obesity.
Role: Principal Investigator
Amount: $12,500

Center of Large Data Research (Tarlov & Eisenberg) 10/1/17 – 9/31/18
Development and validation of a mobility disability algorithm.
The purpose of this pilot project is to develop and validate an algorithm that identifies people with mobility disability using electronic healthcare data.
Role: Co-Principal Investigator
Amount: $25,000

National Association of Chronic Disease Directors (UIC PI) 7/1/2016- 5/30/2018
Evaluation of the Disability and Health Communities Project
The purpose was to evaluate a pilot project of 10 communities working to implement policy, systems, and environmental changes.
Role: Lead Evaluator
Sub-award amount: $29,800

Idaho Department of Health and Family Services (Owen) 7/1/17 – 6/30/2018
Evaluation of Idaho's Non-emergency medical transportation (NEMT) services
The purpose of the project was to evaluate the quality and access to care for Medicaid recipients in Idaho. The independent evaluation will include a pre-post survey and analysis of NEMT data and contracts.
Role: Lead data analyst

Illinois Department of Public Health (Heller) 7/1/11 – 7/31/16
State of Illinois Department of Healthcare and Family Service (HFS)
"An Independent Evaluation of Illinois Integrated Care Program"

The purpose of this project is to evaluate a pilot ICP program for Illinois Medicaid recipients. The independent evaluation will examine access to health care services, member satisfaction and cost effectiveness under Managed Care Organizations.
Role: Analyst

Rehabilitation Institute of Chicago (UIC PI) 11/1/13 – 10/31/16
OttoBock (private)
“Micro-processor controlled Knee-Ankle-Foot Orthosis (C-Brace) vs. Stance-control Knee-Ankle-Foot Orthosis (SCO): Functional Outcomes in Individuals with Lower Extremity Impairments due to Neurological Disease” The purpose of this project is to assess the level of community participation of people with amputations pre and post being given a microprocessor foot by analyzing data collected through GPS data loggers to allow for an objective assessment of community participation and neighborhood travel patterns.
Role: Co- Investigator
Amount: $36,996

Lakeshore Foundation (UIC PI) 8/1/15 – 3/15/16
National Center for Mobility Management
Design for Disability: Access to Health and Transportation
The purpose of this sub-ward was to provide advice and feedback for a community design charrette about transportation for people with disabilities, facilitated groups at a stakeholder charrette and develop maps on demographics and transportation for people with disabilities in Birmingham, AL.
Role: Consultant
Amount: $6,000

CDC-BAA 2011-N-13396 (UIC PI) 8/22/11 – 8/21/14
Centers for Disease Control and Prevention (CDC), National Center on Birth Defects and Developmental Disabilities (NCBDDD), Disability and Health Branch
Development of a Community Health Inclusion Index
The purpose of this project is to develop a Community Health Inclusion Index for determining aspects of the community that are critical for improving healthy, active living for people with disabilities. It will provide communities with the ability to measure how well they support healthy, active living for all members of the community, including people with disabilities.
Role: Took over Principal Investigator when Dr. James Rimmer left in 2012
Amount: $1,000,000

Rehabilitation Institute of Chicago (UIC PI) 8/1/11 – 12/31/13
OttoBock (private)
“Microprocessor Knee vs. Mechanical Knee: Impact on Functional Outcomes in Dysvascular Transfemoral Amputees” The purpose of this project is to assess the level of community participation of people with amputations pre and post being given a microprocessor knee by analyzing data collected through GPS data loggers to allow for an objective assessment of community participation and neighborhood travel patterns.
Role: Co-Principal Investigator

PEER REVIEWER

I have been a peer reviewer for the following journals and grantors:

- American Journal of Preventive Medicine
- Biomed Central (BMC) Public Health
- British Medical Journal (BMJ) Open

- Preventive Medicine Reports
- Journal of Transport and Health
- Journal of Housing and the Built Environment
- Cities & Health
- Planning Practice and Research
- Patient Centered Outcomes Research Institute (PCORI)
- Center for Large Data Research (CLDR)

EXPERT PANELS

I have served on several expert panels that include:

- Azavea Inc. NIH Small Business Innovation Research (SBIR) (2013) - *Promoting Regular Physical Activity for Older Adults through "Wayfinding" technology*
    - I provided guidance on development of a wayfinding smart phone application that could be used by older adults to become more physically active in the local neighborhoods. The project was funded for the first phase of the NIH SBIR.
- The CDC Division of Community Health (2012) - Built *Environment Assessment tool* for walking and biking to be used in Community Transformation Grants.
    - I served on an expert working group to identify the factors that should be used in assessments of the built environment and represented aspects of the built environment that would be important for people with disabilities.
- North Carolina Department of Public Health (2011)- The *North Carolina Guide to Incorporating Health Considerations into Comprehensive Plans*
    - I served on an expert working for developing the guide and provided recommendations related to disability and health.
- The National Center on Health Physical Activity and Disability (NCHPAD) to develop a *Community Health Inclusion Sustainability Plan (CHISP)*
    - I served as an expert panel member to develop recommendations on how include individuals with disabilities in community health coalitions.

ADVISORY BOARDS

- Cook County Forest Preserve ADA Advisory Committee: 2018-present
- Statewide Independent Living Council of Illinois- Housing Advisory Committee 2015-2017
- Chicago Transportation Authority ADA Advisory Board: 2010-2013
- UIC Chancellor's Committee on the Status of People with Disabilities 2010-2015
- GeoAccess Work Group: **Data-Enabled Travel:** How Geo-Data Can Support Inclusive Transportation, Tourism, and Navigation through Communities: *g3ict.org/download/p/fileId_831/productId_161*

COMMITTEES/MEMBERSHIPS

- CDC Physical Activity Policy Research Network, Older Adults Working group, 2015-present
- American Public Health Association (APHA) Disability Section, 2010 - present

GUEST LECTURES

- DHD 541, Guest lecture for Dr. Hasnain on quantitative inquiry and research methods Fall 2016-2018
- DHD 202, Guest lecture for Dr. Grossman on accessible cities and measurement, Spring 2018

STUDENT COMMITTEES

- Jacqueline Kish Beck, PhD candidate, prelim committee (2017)
- Kristen Salkas, PhD candidate, prelim committee (2016)

- Amie Lulinski Norris, PhD Dissertation Committee member, title: *Community Capacity to Provide Mental/Behavioral Health Services to People with Developmental Disabilities* (2014)

VOLUNTEER

- Equip for Equality, Voting Access Project, coordinate UIC student training, 2016-2018