Health and Employment for Adults with Serious Mental Illness:

An Examination of Physical Health Conditions, Healthcare Utilization,

Health-Related Quality of Life, and Employment

By

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Abstract

Mounting chronic condition rates, elevated healthcare spending, and increased attention to the importance of structural and social health determinants, have magnified attention to disparities in health and healthcare in the United States. Adults with serious mental illness (SMI) have higher rates of many chronic physical health conditions when compared to the general U.S. population, and co-occurring physical and mental health conditions are associated with higher use of emergency healthcare services and higher healthcare costs compared to those with only one condition. At the same time, while adults with SMI express a desire to work, they experience high rates of unemployment. Research indicates that mental health symptoms and mental health care are related to employment for adults with SMI, however there is a need for further inquiry regarding the roles of physical health and healthcare. Drawing on three theoretical perspectives-the social determinants of heath framework, the health as human capital model, and the behavioral model for health service utilization-this dissertation examined relationships between physical health conditions, healthcare, health-related quality of life, and employment for adults with SMI, at both the bivariate and multivariate levels. Direct and indirect relationship were examined using structural equation modeling (n = 645), and findings suggested that individuals with SMI and co-occurring physical health conditions had higher use of healthcare, and lower health-related quality of life, compared to those with SMI only. Further, healthcare receipt and health-related quality of life mediated relationships between physical health conditions and employment status, and physical health-related quality of life had a stronger relationship with employment than mental health-related quality of life. The findings of this dissertation are discussed, and implications for future research, social work practice, and health policy are provided.

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Chapter 1: Introduction

Chronic physical health conditions present a persistent public health problem in the United States (Ward & Schiller, 2013). Disparities in chronic condition rates and severity have long-plagued minoritized persons of color and the economically disadvantaged (Braveman, 2012; Williams, 2012). Disparate rates of physical health conditions have also been increasingly noted among individuals with serious mental illness (SMI; e.g., DeHert et al., 2011; Razzano et al., 2015), and individuals with SMI have higher rates of mortality and decreased life expectancy (Colton & Manderscheid, 2006). Co-occurring mental and physical health conditions are associated with poor socioeconomic outcomes related to employment and income (e.g., McIntyre et al., 2006; Ruzickova, Slaney, Garnham, & Alda, 2003) and increased healthcare costs and utilization (e.g., Choi, Lee, Matejkowski, & Baek, 2014; Shen, Sambamoorthi, & Rust, 2008).

Total healthcare spending in the U.S. amounted to $3.2 trillion in 2015, a 5.8% increase from 2014 (Centers for Medicare and Medicaid Services [CMS], 2016). Healthcare spending is expected to increase by an average of 5.8% annually between 2015 and 2025 (CMS, 2016). These mounting healthcare costs are attributed to advances in costly technology, worsening health status (e.g., obesity), increased health insurance spending and access to specialty healthcare, and to a smaller extent, the aging of the U.S. population (Ginsburg, 2008).

Contributing to the rise in total healthcare spending are co-occurring SMI and physical health conditions, which are associated with higher utilization of emergency services (e.g., Egede, 2007; Shen et al., 2008), which tend to be more costly than other forms of healthcare utilization (CMS, 2015), as well as overall higher healthcare expenditures (e.g., Choi et al., 2014; Lee, Rothbard, & Choi, 2015). These healthcare utilization and spending patterns increase individual and societal healthcare costs, however they are also necessary for the attainment of good and stable health (Andersen, 1995), and may promote favorable economic well-being (Grossman, 1972).

Literature on relationships between health and employment suggests that healthcare utilization may improve employment rates among individuals with SMI (Grossman, 1972). Employment is closely tied to an individual's income, savings, and wealth potentials, and unemployment increases societal costs, such as the provision of unearned income (Chan, Hirai, & Tsoi, 2015; Leddy, Stefanovics, & Rosenheck, 2014). Individuals with serious mental illness (SMI) have high unemployment rates (Luciano & Meara, 2014), and elevated rates of receipt of Social Security Disability Income (SSDI) and Supplemental Security Income (SSI) (Pratt, 2012). While unemployment status among members of this group is high, employment is often a goal of individuals with SMI (e.g., Westcott, Waghorn, McLean, Statham, & Mowry, 2015). Research on predictors of employment for individuals with SMI has primarily focused on clinical indicators (e.g. psychiatric hospitalization, symptomology, and substance abuse), medication, cognitive functioning, and education (e.g., Ellinson, Houck, & Pincus, 2007; Luciano & Meara, 2014; Luo, Cowell, Musuda, Novak, & Johnson, 2010). While these factors are clearly important, employment-research for individuals with mental health conditions rarely considers factors related to physical health, even though physical health is also known to influence employment (e.g., Chirikos & Nestel, 1985; Kahn, 1998).

Theories that explain relationships between health determinants, health, and poor social and economic outcomes focus on individual health choices/behaviors as well as social and structural determinants. Structural determinants are those that reflect systematically unequal distributions of power, prestige, and resources in a society (Solar & Irwin, 2010). Examples of structural determinants that affect health include socioeconomic status, sex, race, and ethnicity.

Within the theoretical and empirical literature, minoritized persons of color are often compared to White individuals. Further, terms used to reflect the categorization of racial and ethnic backgrounds vary. For example, the term ‘non-White’ is commonly used to group several categories of minoritized persons of color together, and the terms ‘Black’ and ‘African American’ are often used interchangeably, irrespective of differences between these identities. Similarly, researchers have long-struggled to measure and discuss sex and gender differences, often confusing or over-simplifying the terms (Johnson & Repta, 2012). ‘Sex’ refers to biological characteristics of males and females, whereas gender is non-binary and refers to psychological and sociocultural characteristics assigned to these biological categories by either the individual or outside observers (Deaux, 1985; Johnson & Repta, 2012; Unger, 1979). Within this dissertation, discussion of the theoretical and empirical literature on racial, ethnic, sex, and gender differences in health, healthcare utilization, and employment, reflects the language used by the cited authors. However, it is important to acknowledge and consider the meanings and appropriate use of these terms, as well as the ‘othering’ of minoritized persons of color suggested by the term ‘non-White’ and by references to White individuals as the normative or ideal group (Johnson et al., 2004).

This dissertation draws from theoretical literature on the social and structural-level determinants that influence health and employment, including contributions from the social determinants of health (SDOH) framework (Solar & Irwin, 2010), Grossman’s (1972) theory on health as human capital, and the behavioral model of health service utilization (Andersen, 1995; Andersen & Newman, 1973). For the purposes of this dissertation, the term “co-occurring conditions” is used to refer to the presence of co-occurring SMI and physical health conditions. Available empirical research provides little insight about the relationships between co-occurring conditions and employment outcomes, and about modifiable factors that intervene between diagnoses and employment outcomes (e.g., healthcare receipt, health-related quality of life) for those with co-occurring conditions. Given a heightened interest in healthcare access following the passage of the Affordable Care Act (2010), and current action and ongoing debates surrounding its possible repeal, it is especially important to explore whether healthcare receipt improves health and employment for individuals with co-occurring conditions. This dissertation proposes the first known study to examine the roles physical health conditions and treatment have on health-related quality of life (HRQOL) and employment for individuals with SMI. This understanding can enhance efforts to remove barriers to employment, improve employment-related outcomes, and reduce dependency on disability income for individuals with SMI.

This dissertation begins by describing the prevalence and structural determinants of co-occurring conditions, and the history and current state of healthcare practice and policy in the U.S., and employment for individuals with SMI. Then, chapter two reviews the theoretical and empirical literature that contributed to the development of this study. This includes an overview of the social determinants of health framework (Solar & Irwin, 2010), behavioral model of health service utilization (Andersen, 1995; Andersen & Newman, 1973), and Grossman's (1972) health as human capital theory, to describe the theoretical mechanisms that guide the dissertation study. The empirical literature on the relationships between co-occurring conditions, healthcare utilization, HRQOL, and employment is also examined. Chapter three presents the methodology for the proposed dissertation, including a description of the data source and study sample, measures, and the data analysis procedures. Finally, the results from the dissertation study are provided in chapter four, and in chapter five, referencing the literature, the findings are discussed and implications for future research and for policy and social work practice are presented.

Prevalence and Structural Determinants of Co-Occurring Conditions

Prevalence. Approximately four percent of individuals in the U.S. are diagnosed with a serious mental illness (SMI), such as bipolar disorder, schizophrenia, or major depression (Center for Behavioral Health Statistics and Quality, 2016). Individuals with SMI experience increased rates of multiple chronic physical health conditions (e.g., Lee, Black, & Held, 2016; Lee et al., 2015), as well as increased prevalence of specific physical health conditions, such as obesity, diabetes mellitus, cardiovascular disease (CVD), hypertension (HTN), coronary heart disease, stroke, and chronic obstructive pulmonary disease (COPD; e.g., DeHert et al., 2011; Lee et al., 2015; Razzano et al., 2015; Smith, Easter, Pollock, Pope, & Wisdom, 2013). For example, among a nationally representative sample of respondents on the 2011 Medical Expenditures Panel Survey (MEPS), Lee et al. (2015) found that 31.8% of individuals with SMI reported a diagnosis of HTN (compared to 17.6% for individuals without SMI), 28.4% a diagnosis of COPD (compared to 9% for individuals without SMI), and 15.1% reported a diabetes diagnosis (compared to 6.6% for individuals without SMI). Further, a study of 457 adults receiving services at community mental health centers (CMHCs) in four U.S. states indicated participants with SMI had statistically significant increased prevalence rates for a number of chronic physical health conditions (e.g., asthma, stroke, emphysema, diabetes, heart condition) compared to the general U.S. population (Razzano et al., 2015).

The increased rates of chronic physical health conditions among individuals with SMI are not unique to the U.S. A recent international study of seventeen countries that administer the World Mental Health survey (N=47,609) found that individuals with any mood disorder or any anxiety disorder had increased odds of being diagnosed with arthritis, chronic pain, heart disease, stroke, HTN, diabetes (mood disorder only), asthma, chronic lung disease (mood disorder only), and peptic ulcer (Scott et al., 2016). The World Mental Health surveys are cross-sectional surveys conducted in four low-lower middle income countries (e.g., Colombia, Iraq), three upper middle income countries (e.g., Mexico, Romania), and 11 high income countries (e.g., Japan, U.S., The Netherlands). Further, a study of Scottish individuals using administrative health system data ($N = 1,751,841$) found those with bipolar disorder had increased odds of one, two, or 'three or more' physical health comorbidities, and increased rates of fifteen specific physical health conditions (Smith et al., 2013).

Structural determinants. Structural determinants place individuals at increased risk for health conditions and research indicates that disparities based on these structural determinants are also observed in terms of the presence of co-occurring conditions. Research suggests females, individuals of low SES, and minoritized persons of color are at increased risk for having co-occurring conditions (e.g., Cabassa et al., 2013; McEvoy et al., 2005; Razzano et al., 2015). For example, Razzano et al. (2015) examined relationships between gender, Medicaid status (i.e., SES), race, and specific physical health conditions among adults with SMI receiving services at CMHCs in New Jersey, Illinois, Maryland, and Georgia ($N = 457$). Females were approximately two times more likely to be diagnosed with diabetes than men ($OR=1.9$, $p<.05$), and having Medicaid as sole payer source increased the likelihood for an asthma diagnosis ($OR=1.6$, $p<.05$) but decreased the likelihood for high cholesterol ($OR=.49$, $p<.01$). Additionally, non-White individuals with SMI had increased odds for HTN ($OR=1.8$, $p<.01$) or diabetes ($OR=1.9$, $p<.05$), compared to White participants with SMI.

Increased prevalence for co-occurring conditions among females or low-SES individuals was also found by Jones et al. (2004) and McEvoy et al. (2005). Jones et al. (2004) examined the treated-prevalence of physical illness among a representative sample of Medicaid-eligible persons with SMI in Massachusetts (N = 147). Females with SMI were more likely to have been treated for metabolic disorder (X^2=9.38, p<.01), skeletal and connective tissue disorders (X^2=7.74, p<.01), eye conditions (X^2=6.6, p=.01), and genital conditions (X^2=10.6, p=.001), compared to men with SMI. Additionally, individuals with SMI of low SES were more likely to be treated for gastrointestinal disease, compared to those of high SES (X^2=5.42, p<.05). McEvoy et al. (2005) used baseline results from the Clinical Antipsychotics Trials of Intervention Effectiveness (CATIE), and matched comparisons to nationally-representative data, to examine metabolic syndrome among individuals with schizophrenia (N = 1460). Females had increased prevalence of metabolic syndrome compared to men (X^2=13.18, p<.001). Disparities were also observed in multivariate logistic regression models: Females in the CATIE trials (i.e., diagnosed with schizophrenia) had approximately 2.4 greater odds for metabolic disorder compared to the general U.S. population, whereas men in the CATIE trials had approximately 1.8 greater odds (McEvoy et al., 2005).

Disparities based on sex and socioeconomic status were observed in studies using the Primary Care Clinical Informatics Unit dataset, which provides health-related data for Scottish individuals (N = 1,751,841). Barnett et al. (2012), found females were more likely to report a co-occurring condition (10.2% vs. 6.4%, p<.0001), and the prevalence of co-occurring conditions increased as SES decreased (p<.0001). Smith et al. (2013) examined the relationship between sex and co-occurring physical health conditions among individuals with bipolar disorder (n = 2,582). Approximately 64% of adults with bipolar disorder had at least one co-occurring physical health condition, compared to 44% of adults without bipolar disorder (p<.001), and women with bipolar disorder were significantly more likely to have three or more co-occurring physical health conditions compared to men (25% vs. 17%, p<.001).

In addition to disparities based on race found by Razzano et al. (2015), disparities in co-occurring condition rates for African American and Hispanic individuals have been documented by Cabassa et al. (2013), McEvoy et al. (2005), and Ortega, Feldman, Canino, Steinman, & Alegría (2006). Using data from the National Epidemiological Survey on Alcohol and Related Conditions (N = 33,107), Cabassa et al. (2013) found African American respondents with a psychiatric disorder had significantly higher odds of having one chronic medical condition (OR=1.24) and two or more chronic medical conditions (OR=1.36), compared to White respondents with a psychiatric disorder, however no such relationship was noted for Hispanic individuals. Racial and ethnic disparities, however, may relate to the specific mental and physical health diagnoses being investigated, and within-group variations may exist. For example, CATIE results found Black individuals with schizophrenia were significantly less likely (X^2=14.83, p<.001) to have comorbid metabolic syndrome than White individuals, and these findings were also observed when compared to the general U.S. population (McEvoy et al., 2005). Analysis of the National Latino and Asian American Study by Ortega et al. (2006) investigated disparities in co-occurring physical health conditions among Latino subgroups with depression or anxiety (N = 2554). For the full Latino sample, any anxiety disorder increased the odds for diabetes (OR=2.59, p<.01) and cardiovascular disease (OR=1.96, p<.01), and any depressive disorder increased the odds for asthma (OR=1.97, p<.01). In terms of anxiety, Puerto Ricans had increased odds for cardiovascular disease (OR=2.2, p<.05), Cubans for diabetes (2.08, p<.05), and Mexicans for diabetes (OR=3.23, p<.01) and cardiovascular disease (OR=2.08, p<.01). For depression, Puerto Ricans had increased odds for asthma (OR=1.90, p<.05) and decreased odds for cardiovascular disease (OR=.52, p<.05), Mexicans had increased odds for asthma (OR=2.95, p<.05, and there were no significant relationships for Cubans.

Summary. In sum, the existing evidence underscores that persons with SMI are likely to encounter significant physical health challenges, and the risk for co-occurring chronic physical health conditions, and for multiple chronic physical health conditions, is greater when structural factors are involved. Females are more likely to have co-occurring conditions, in particular having elevated prevalence for diabetes. Low-SES individuals with SMI are more likely to report co-occurring physical health conditions, and racial and ethnic disparities in co-occurring condition rates, and specific physical health conditions, are also evident. Access to, and use of, quality and comprehensive healthcare that considers both the mental and physical health of individuals with SMI, as well as the structural aspects of health, may help to ameliorate the risk for co-occurring conditions. At the same time, health and healthcare policies, such as the ACA, have the potential to mitigate the effect of SES on healthcare access and utilization, and improve access to healthcare and health for individuals with co-occurring conditions.

Clinical and Social Determinant Approaches to Healthcare

While it has long been recognized that social and environmental determinants are related to individual and public health, until recently, attempts to improve health in the U.S. have often focused on clinical interventions. Even the field of public health, known for its focus on social and environmental determinants, focused on clinical and laboratory aspects of health and disease for much of the early and mid-20th century (Fairchild, Rosner, Colgrove, Bayer, & Fried, 2010).

In addition to technological and pharmaceutical advances in the treatment of medical conditions, efforts to improve health through clinical care include the development and enforcement of rigorous healthcare quality standards, improved access to healthcare through the provision of health insurance, and changes to healthcare delivery systems (e.g., managed care, integrated healthcare).

Evolution of clinical healthcare in the United States. Following the discovery of the germ in the late 19th century, efforts to improve health centered on laboratory science, including the development of vaccines and antibiotics. Science and medicine were held in high regard, and the hospital became the center of medical treatment (Fairchild et al., 2010). Much attention was placed on the quality and safety of care received in hospital settings, and in 1952 the Joint Commission on Accreditation of Hospitals was formed (Luce, Bindman, & Lee, 1994). Access to clinical care, however, was not equal. Prior to the 20th century, poorer Americans received care in hospitals, while wealthier individuals received care from private doctors (Emanuel, 2015). The discovery of the germ, surgery performed under anesthesia, the development of sterile and antiseptic procedures, and the use of X-ray as a diagnostic tool, lead to hospitals becoming the standard for medical care (Emanuel, 2015). The nation-wide shift to hospital care however, increased costs for medical care, which many could not afford. Consequently, a multifaceted approach to healthcare financing developed over time to help ease the burden of healthcare costs.

Motivated by the wide-spread economic hardship that occurred during the Great Depression, health insurance, first designed as pre-paid hospital and physician plans, emerged as a way to help fund medical care beginning in 1929 (Emanuel, 2015). These pre-paid plans, which later became known as Blue Cross (hospital) and Blue Shield (physician) plans in 1939, charged the same premium to all individuals regardless of age and health status, and were primarily sold through large employers to minimize the effect of adverse selection (Emanuel, 2015). When commercial insurance companies saw the success of Blue Cross and Blue Shield plans, they began to add health insurance as an option, and in 1950 nearly two-thirds of working adults had health insurance for hospital stays (Emanuel, 2015). At the policy-level, the Hill-

Burton Act of 1946 (Policy Health Service Act, 1976), the first federally-funded healthcare act, provided support for hospital construction in poorer states, and in 1954 the IRS exempted health insurance costs from payroll taxes. This lead to the institutionalization of employer-based health insurance in the U.S. and was an advantage to many individuals, but policy-makers soon realized that the elderly were excluded given that they were no longer in the workforce, leading to the eventual development of Medicare in 1965 (Emanuel, 2015).

With improved access to health insurance, individuals in the U.S. had increased access to primary and specialty healthcare. In turn, healthcare spending increased and competition among medical providers ensued, prompting solo-physicians to form physician groups, and hospitals to grow into large systems (Luce et al., 1994). Managed healthcare, which uses protocols/clinical guidelines and utilization review to manage provider decision making, emerged as an innovative healthcare delivery method with the potential to decrease healthcare costs and improve patient health outcomes (Gordon, Baker, Roper, & Omenn, 1996). Later, prompted by some successes of managed care and encouraged by the ACA (2010), two new models of healthcare prevailed: accountable care organizations (ACOs) and person-centered medical homes (PCMH). ACOs continued the managed care practice of utilization and risk management but encouraged structured medical provider integration and were separate from the business of health insurance (Dove, Weaver, & Lewin, 2009; Fulton, Pegany, Keolanui, & Scheffler, 2015). While developed around the same time, PCMHs separated themselves from ACOs as a transformative healthcare delivery method that centered on primary care and focused on patient needs rather than being business-driven (Stange et al., 2010). At present, motivated in part by rising healthcare costs and increased attention on the prevalence of co-occurring physical and mental health conditions, integration of behavioral and physical healthcare is becoming the norm by demonstrating promising results for improving mental and physical health outcomes (e.g. Gilmer, Henwood, Goode, Sarkin, & Innes-Gomberg, 2016; Shane, Nguyen-Hoang, Bentler, Damiano, & Momany, 2016; Unützer, Harbin, Schoenbaum, & Druss, 2013).

While clinical healthcare in the U.S. has undergone significant reform during the 20th and early 21st centuries, chronic diseases rates continue to rise, and healthcare costs continue to increase (e.g., CMS, 2016; Ward & Schiller, 2013). Clearly, clinical healthcare alone is not enough to combat the many health concerns and disparities that plague the U.S. population (e.g., Braveman, 2012; Williams, 2012). While scholars and medical providers alike acknowledge relationships between social determinants and health outcomes, less attention has been paid to intervening outside of the clinical setting. The following section reviews the evolution of empirical knowledge and action regarding social determinants of health in the U.S. during the 20th century.

The history of social determinants of health in the United States. Increased population density in urban areas related to industrialization and mass immigration brought challenges related to poverty and sanitation in the late 19th and early 20th centuries (Trattner, 2007). Scholars identified a connection between social position and health (e.g., Britten, 1934; Faris & Dunham, 1939; Knopf, 1914), and public health officials and social reformers successfully advocated for housing, food, and work regulations to improve public health, including requirements related to housing density and the need for all new housing structures to have indoor plumbing (Fairchild et al., 2010). Later, attention turned to examining causal pathways between social position and health (e.g., Dohrenwend & Dohrenwend, 1967; Dohrenwend et al., 1992; Turner & Wagenfeld, 1967), as well as identifying the likely health consequences associated with poverty and possible strategies to mitigate that relationship (e.g., Bamberger, 1966; James, 1965). However, while scholars were in agreement that a connection existed, policies and funding were directed toward improving clinical healthcare (Fairchild et al., 2010), and most of the literature remained focused on poverty, with minimal application to the general population that was not living in poverty (Braveman, Egerter, & Williams, 2011).

The ‘Black Report’ was published in 1980, and brought new attention to social determinants of health, arguing that improvements to education, housing, and social welfare would improve health in the United Kingdom (Black, Morris, Smith, & Townsend, 1980). This report spurred discussions worldwide, and in 2004 the World Health Organization (WHO) announced the creation of the Commission on Social Determinants of Health, charging it with responsibility for investigating pathways from root causes to health status differences, identifying where and how health inequalities should be addressed, and culminating with the creation of a comprehensive SDOH framework (Marmot, 2005; Solar & Irwin, 2010). The ‘Black Report’ and the Commission on Social Determinants of Health are considered the impetus for the focus on social determinants of health across the world, including in the United States.

It wasn’t until the early 1990s that studies on social determinants of health began to appear in the academic literature in the U.S., and it was another decade before the amount of literature on social determinants of health began a steady upward climb (Braveman et al., 2011). In addition to garnering more attention in the academic literature, macro-level change also occurred. Notably, in 1997 the MacArthur Foundation Network on Socioeconomic Status and Health was formed to examine relationships between socioeconomic position and health (University of California San Francisco, n.d.), and in 2008 the Robert Wood Johnson Foundation (RWJF) formed the Commission to Build a Healthier America (RWJF, n.d.). Additionally, social determinants of health was included as a priority topic in the Office of Disease Prevention and Health Promotion's Healthy People 2020 initiative (Centers for Disease Control and Prevention, 2011). This designation elevated the place of social determinants of health in the U.S. healthcare system, and among health researchers.

While attention to social determinants of health in the U.S. has increased, there is still much work to be done. A single intervention is unlikely to be the silver bullet: A multifaceted approach is needed to intervene at the policy, community, and individual levels, to improve social determinants of health (Braveman et al., 2011). The Centers for Medicare and Medicaid Services recently changed their Medicaid managed care rules to financially incentivize health plans that include non-clinical services as covered services, as well as encouraged states to improve care coordination and home and community-based services (Machledt, 2017). This rule-change serves as one example of healthcare transformations aimed at integrating clinical and social healthcare within the U.S. healthcare systems.

Contributions of the social work profession. During the late 19th and early 20th centuries, a cyclical relationship between poverty and communicable disease was observed: poverty increased the likelihood of communicable disease, and illness led to poverty due to the creation of financial hardship (Fairchild et al., 2010). Given that social workers were already in the community addressing conditions related to poverty (e.g., Hull House, Charity Organization Societies), they played a prominent role in the areas of public education and health reform (Fairchild et al., 2010). For example, in 1903, social workers played a lead role in responding to the tuberculosis epidemic, through the completion of the first comprehensive analysis of tuberculosis (Trattner, 2007). The Committee on the Prevention of Tuberculosis, organized within the Charity Organization Society of New York, investigated the severity, incidence, and symptoms of tuberculosis. The committee sought to explain how it could be stopped or prevented, with the goal of increasing public awareness. For decades, social workers played an active role in the prevention and awareness of communicable disease, such as diphtheria and syphilis.

Social workers emerged in the hospital setting in 1905 when Dr. Richard Cabot, a physician at Massachusetts General Hospital, brought social workers into the hospital to help patients in the outpatient clinics with the social problems related to their medical treatment (Bartlett, 1975). This revolutionary service was not fully supported by the hospital, and in fact Dr. Cabot personally raised all the funds needed for the salaries and expenses of the program, and he continued to support the social work program financially for 14 years (Bartlett, 1975). Hospital social work quickly grew in popularity and acceptance: By 1913 there were over 100 U.S. hospitals with social service departments, and in 1924 this number reached 420 (Praglin, 2007). Hospital social work's early contributions to a complementary clinical and social approach to healthcare included a study that sought to establish a causal relationship between illness/bodily dysfunctions and social factors (Sedgwick, 2012; Thornton & Knauth, 1937). This research brought a new respect for the abilities of social workers in healthcare, and found that social factors played an important role in the health of patients with chronic and recurrent health problems (Thornton & Knauth, 1937). Another contribution of social work to a complementary social and clinical approach to healthcare in the hospital setting is documented in Ethel Cohen's novel creation of hospital rounds that focused on the social context of illnesses (Praglin, 2007). Social workers' roles in clinical settings continued to expand overtime (Craig & Muskat, 2013; Gregorian, 2005; Stanhope, Videka, Thorning, & McKay, 2015), and dual-degree programs in public health and social work are now offered in a number of U.S. universities (Ruth et al., 2008). Today, social workers have a presence across public health and clinical healthcare settings, helping to bridge the social and clinical aspects of healthcare.

Summary. The rise in clinical care and the focus on laboratory science set clinical medicine at the forefront, however, as health disparities persisted, increased attention was placed on factors that seemed to influence health (i.e., social determinants) and that existed outside of clinical medicine. It is likely that individual and public health improvements are best achieved using a complementary approach that acknowledges both the clinical and social determinants that affect health, including co-occurring mental and physical health conditions. The social work profession has long-been involved in addressing the social determinants of health (Bartlett, 1975; Sedgwick, 2012; Thornton & Knauth, 1937), and continues to be actively involved in research related to social determinants of health (e.g., Cabassa et al., 2013), and practice with marginalized populations who are likely to be affected by social determinants (NASW, 2018). Still, the importance of clinical healthcare cannot be ignored. In the U.S., health insurance is the primary method for individuals to access and pay for clinical healthcare. Policy-level interventions aimed at improving access to health insurance and expanding the types of healthcare services reimbursable by health insurance may help to increase access to healthcare, and improve clinical and social health outcomes for marginalized populations.

Healthcare Reform through the Affordable Care Act

After much deliberation, and with mixed support, President Obama signed the ACA into law on March 23, 2010. Minutes after the ACA became law, several lawsuits were filed challenging its constitutionality (Curfman, Abel, & Landers, 2012). On June 28, 2012, the Supreme Court upheld the ACA as a whole, but ruled that the requirement that states expand Medicaid was coercive (*National Federation of Independent Businesses et al. v. Sebelius*, 2012).

As a result, states were authorized to make individual decisions on whether to expand Medicaid, with no threat of federal consequences for non-adoption. The provisions contained in the ACA (2010) are vast and comprehensive, targeting health care improvements at the individual, provider, and system levels. The ACA (2010) consists of ten titles (i.e. chapters) that cover many aspects of health care (e.g., quality, affordability, and efficiency of health care, prevention of chronic disease, health care workforce development); as discussed previously, this section focuses on title two, which contains provisions related to Medicaid expansion and Medicaid health homes.

Medicaid expansion. The expansion of Medicaid provides coverage to adults under age 65 with an annual income below 138% of the federal poverty line (FPL; ACA, 2010). However, as a result of *National Federation of Independent Businesses et al. v. Sebelius* (2012), expanded adult coverage only applies to individuals living in states that elected to expand Medicaid coverage under the ACA. As of January 2017, thirty-one states, and the District of Columbia, have expanded Medicaid under the ACA (Kaiser Family Foundation, 2017).

As expected, access to health insurance has improved in states that expanded Medicaid eligibility (Kaiser Family Foundation, 2016b). Medicaid expansion is linked to improvements in primary care access, medication adherence, emergency department and outpatient health care utilization, screening and treatment, quality of care, and self-reported health (Kaufman, Chen, Fonseca, & McPhaul, 2015; Sommers, Blendon, Orav, & Epstein, 2016; Thomas, Shartzer, Kurth, & Hall, 2017). Importantly, research also indicates that post-ACA Medicaid expansion was associated with increased employment rates among individuals with mental health conditions (Thomas et al., 2018). Thus, Medicaid expansion can improve access to healthcare, other health outcomes, and possibly even employment, for marginalized low-income adults.

However, given that each state can choose whether to expand Medicaid coverage, insurance-related disparities in healthcare access and treatment for individuals living in poverty are still present. Individuals with co-occurring conditions who weren't previously eligible for Medicaid may now be eligible for it, if they reside in a state that expanded Medicaid under the ACA (2010). Expanded Medicaid coverage reduces structural barriers to healthcare for individuals with co-occurring conditions, which in turn may improve their health and economic well-being.

Medicaid health homes. Medicaid health homes provide comprehensive healthcare and support for Medicaid-eligible individuals with chronic conditions (ACA, 2010). The term 'health home' refers to a set of services (e.g., care management, health promotion, education and support) provided under the direction of a healthcare provider or team, not to a specific location where all medical care is received. A health home can be embedded in a variety of settings (e.g., physician office, hospital, and community mental health center), and includes a multidisciplinary team of professionals (e.g., physicians, nurses, social workers). An individual may receive health home services if they are eligible for Medicaid in their state, and 1) have at least two chronic conditions (e.g., mental health conditions, diabetes, heart disease, Body Mass Index over 25), 2) one chronic condition and are at risk for developing a second condition, or 3) are diagnosed with a serious and persistent mental health condition (SMI). While the varied criteria for eligibility expands access to health home services, the requirement that members be eligible for Medicaid perpetuates health disparities between expanding and non-expanding states.

Importantly, the provision that any Medicaid-eligible individual with SMI qualifies for health home membership, and that health homes may be embedded within behavioral health settings (ACA, 2010), provides improved access to healthcare monitoring and treatment, opportunities for prevention of physical health comorbidities, and enhanced treatment for chronic conditions. Preliminary evidence indicates that for individuals with SMI, Medicaid health homes may improve screening and diagnosis for chronic conditions, physical health care access, physical health status and mental health recovery, medication adherence, HTN, and reduce Medicaid spending and emergency department use (e.g., Druss et al., 2017; Gilmer et al., 2016; Shane et al., 2016; Tepper et al., 2017). Taken together, Medicaid health homes have the potential to reduce structural barriers related to healthcare access and receipt, improve individual health and well-being, and reduce healthcare costs related to mental and physical health conditions.

Threat of ACA repeal. Following the end of President Obama's tenure, threats of 'repeal and replace' have been heard from President Trump and Congress. While efforts to repeal the ACA failed during the summer of 2017 (Seervai & Blumenthal, 2018), changes to some components of the ACA have occurred, and conversations will likely continue with additional changes to come. Though not related to Medicaid expansion or Medicaid health homes, one notable change is the elimination of the individual health insurance mandate penalty, which was pushed through as part of tax reform policy (Seervai & Blumenthal, 2018). Importantly, the individual mandate to have health insurance was not repealed, however as of 2019 there will no longer be a financial penalty imposed.

More recently, the U.S. Department of Health and Human Services (DHHS) allowed for states to submit Medicaid Section 1115 demonstration projects that would include an employment requirement for Medicaid recipients (Centers for Medicare and Medicaid Services, 2018a). As of January 30, 2018, one state (Kentucky) had received approval for a work requirement waiver, and ten other states, including Kansas, have submitted proposals to DHHS for a work requirement waiver (Rosenbaum, 2018). While demonstration projects will differ, Kentucky's plan, for example, will transition the majority of non-disabled (i.e., not receiving SSI) adults from the traditional, pregnant woman, and expansion Medicaid programs, into the new Kentucky HEALTH program (Centers for Medicare and Medicaid Services, 2018b). Thus, individuals who recently gained Medicaid coverage as a result of the ACA will experience a change to their ongoing eligibility and benefits, and will be forced to become part of an experimental demonstration project. Kentucky HEALTH will include health-related personal responsibility measures (e.g., cost-sharing measures, health incentives/disincentives) and a requirement that all able-bodied, working age, adult members participate in 80 hours per month of 'community engagement' which may include volunteer work, job search activities, education, caretaking of dependents (limited to one parent in household), or paid employment (Centers for Medicare and Medicaid Services, 2018c). The health and employment related consequences, either positive or negative, of this change in Medicaid policy will not be known for a few years. However, this waiver opportunity suggests an interest in health insurance and healthcare that places more onus on the individual for their personal health and economic well-being. The inclusion of a work mandate as a condition of Medicaid coverage could have drastic negative consequences for individuals with mental health conditions given the challenges they face with not only obtaining employment, and also with maintaining employment.

Employment for Individuals with SMI

Employment improves the well-being of individuals with SMI and has benefits for broader society. Employment can improve self-esteem and quality of life for individuals with mental health conditions (Abraham, Ganoczy, Yosef, Resnick, & Zivin, 2014; Bond et al., 2001), as well as reduce the average costs and utilization for outpatient mental health services and institutional stays (Bush, Drake, Xie, McHugo, & Haslett, 2009). Unemployment can increase dependence on unearned income (Chan et al., 2015; Leddy et al., 2014), often criticized for having high economic costs to society. Individuals with SMI experience higher rates of unemployment than the general population, are less likely to transition out of unemployment, experience more time off work, work fewer hours per week, and have lower incomes (e.g., Baldwin & Marcus, 2014; Ettner, Frank, & Kessler, 1997; Lanuza, 2013; Luciano & Meara, 2014; Luo et al., 2010). As a result, individuals with SMI are more likely to receive conditional income, such as TANF, food stamps, and SSI (e.g., Luciano, Bond, & Drake, 2014). A study by Pratt (2012) found that among non-institutionalized adults with serious mental illness, 18.8% reported receipt of SSDI and 16.2% reported receipt of SSI. Insel (2008) calculated that in 2002, disability benefits from SSI and SSDI accounted for an economic burden of approximately $24.3 billion among adults with SMI in the U.S., an increase from $16.4 billion ten years prior in 1992. While unemployment among individuals with mental health conditions is high, they desire employment (e.g., Westcott et al., 2015), and employment is beneficial for an individual's self-esteem, mental health symptomology, and life satisfaction, even if the individual has a SMI (Luciano et al., 2014). Over time, employment opportunities and rates for adults with SMI have improved due to changing attitudes towards adults with SMI, policies, and supportive employment services. However, systemic, employer, and individual-level barriers continue to make it difficult for adults with SMI to obtain and retain employment. The following section briefly reviews the history of employment for adults with SMI in the U.S., describes the current employment climate for adults with SMI, and discusses the relevance of employment for adults with SMI to the social work profession.

History of employment for adults with SMI. While late 19th and early 20th century psychiatric treatment for persons with mental health conditions often included structured activities and work, it wasn't until the 1943 Vocational Rehabilitation Act that persons with mental health conditions were actively encouraged to enter the competitive workforce (Anthony & Liberman, 1986). The extension of vocational rehabilitation services to persons with mental health conditions provided support for pro-employment attitudes and led to the development of paid work that was subcontracted to psychiatric hospitals (Anthony & Liberman, 1986). Attitudes and services were further enhanced following the nation-wide shift to community-based treatment for persons with mental health conditions. Deinstitutionalization began in the late 1950s but did not reach its peak until the 1970s, and was accompanied by federal funding for States to provide mental health treatment in community settings (Pratt & Gill, 2005). Early community mental health services, combined with the availability of new antipsychotic medications, reduced psychotic features and allowed persons with mental health conditions to be more successful in the community (Pratt & Gill, 2005). Psychosocial centers, established by previously-hospitalized persons with mental health conditions, additionally provided mutual support and assistance with obtaining employment (Anthony & Liberman, 1986). Following deinstitutionalization, research findings pointed to better employment outcomes for persons treated in their community versus in an institution (Marx, Test, & Stein, 1973), helping to shift attitudes in favor of the employability of persons with mental health conditions.

As community-based treatment modalities evolved, psychiatric rehabilitation became the treatment approach of choice, combining clinical treatment, social treatment, and skills training to enable persons with mental health conditions to successfully live and work in the community (Anthony & Liberman, 1986). Structured vocational skills training programs were developed and demonstrated success (e.g., Jacobs, Kardashian, Kreinbring, Ponder, & Simpson, 1984). As research on vocational skills programming increased, and programs were refined, evidence-based supportive employment programs were developed. One such program, the Individual Placement and Support (IPS) model, was developed in the early 1990s and integrates personalized employment services into mental health treatment (Dartmouth University, 2012). IPS has repeatedly demonstrated effectiveness at improving employment, increasing income, and reducing dependence on disability income for individuals with SMI (e.g., Bond, Xie, & Drake, 2007; Crowther, Marshall, Bond, & Huxley, 2001; Drake, Skinner, Bond, & Goldman, 2009).

Advancements in policy interventions have also improved employment for adults with SMI. In 1956, the social security program was expanded to include individuals with disabilities (Kearney, 2005). The Social Security Administration (SSA) provides incentives that allow individuals receiving SSI/SSDI to return to work without immediate loss of benefits (Social Security Administration, 2016). Federally funded, but state-administered, vocational rehabilitation programs provide a range of employment services (e.g., vocational training, counseling, and job placement) to individuals with SMI (Rehabilitation Services Administration, n.d.). Vocational rehabilitation also works in partnership with IPS programs to provide comprehensive employment supports to individuals with SMI, increasing their likelihood for success.

Another important policy that reduced systemic barriers to employment for individuals with SMI was the Americans with Disabilities Act (ADA; 1990). The ADA went into effect in January 1992 and prohibited discrimination against individuals with disabilities in employment settings, and also required that employers with 15 or more employees make reasonable accommodations (ADA, 1990). Unfortunately, the passage of the ADA didn't translate to the elimination of systemic barriers to employment for individuals with SMI. For example, a study by Scheid (1998) found that following enactment of the ADA, employers often reported being uncomfortable with hiring a person in treatment for depression, a previous psychiatric hospitalization, or on psychiatric medication. Further, the percentages of employers who reported discomfort was much higher for these situations compared to hiring a prospective employee with a learning disability or physical handicap (Scheid, 1998). While the ADA formalized anti-discrimination in employment for individuals with SMI, stigma persists and more work is needed to educate employers regarding the employability of individuals with SMI.

Current employment climate. While improvements to employment services, policies, and attitudes toward the employability of persons with mental health conditions have a favorable impact on employment for individuals with SMI, unemployment rates remain high. Additionally, employer and structural discrimination persist in terms of employment for individuals with SMI (Stuart, 2006). Estimates of unemployment rates among individuals with mental health conditions vary in the literature, however a study by Luciano and Meara (2014) using a nationally-representative sample of the U.S. population, indicated 54.4% of individuals with SMI were unemployed.

Today, the IPS model is commonly implemented at community mental health centers across the U.S., and the world, providing access to supported employment for many individuals with SMI (Dartmouth University, 2012). A recent survey of IPS programs in the U.S. indicated that 38 states had at least one IPS program, with a total of over 500 programs nationwide (Johnson-Kwochka, Bond, Becker, Drake, & Greene, 2017). IPS emphasizes client preferences, and provides continuous employment supports to any individual with SMI who expresses a desire to work (Dartmouth University, 2012). Social workers, who often focus on client strengths to move toward mental health recovery (Carpenter, 2002), are frequently employed as members of the IPS team, and they work with individuals with SMI in hospital and outpatient community mental health settings. The strengths and recovery practice framework that is characteristic of IPS, and often emphasized by social workers is congruent with the belief that individuals with SMI are employable and helps to reduce employment-related stigma.

Given the interest in employment among adults with SMI (e.g., Westcott et al., 2015), it is imperative that barriers to employment are reduced for individuals with SMI. While relationships between clinical indicators, medication, cognitive functioning, education and employment are found in the literature (e.g., Ellinson et al., 2007; Endicott et al., 2014; Luciano & Meara, 2014; Luo et al., 2010; Tse, Chan, Ng, & Yatham, 2014), factors related to physical health among individuals with SMI are rarely considered, even though physical health is known to influence employment (e.g., Birch, Jerrett, & Eyles, 2000; Chirikos & Nestel, 1985; Kahn, 1998). Understanding the roles physical health conditions and treatment play on employment for individuals with SMI can enhance efforts to remove barriers to employment for these individuals, improving their well-being through increased income and improved self-esteem and quality of life (Abraham et al., 2014; Bond et al., 2001). A better appreciation of the relationship between physical health, treatment, and employment is likely to enhance societal economic well-being as well, through reduced costs associated with unearned income (Chan et al., 2015).

Chapter 2: Theoretical and Empirical Literature

This chapter provides an overview of the existing theoretical and empirical literature on relationships between structural determinants, healthcare, health, and employment. These relationships are examined for broader adult populations, and for adults with co-occurring conditions. Three theoretical frameworks are examined: 1) social determinants of health framework, 2) health as human capital theory, 3) and the behavioral model for health service utilization. Additionally, the empirical literature on healthcare utilization, health-related quality of life, and employment for adults with co-occurring conditions is critically examined.

Social Determinants of Health (SDOH) Framework

Historical development. The SDOH framework (Solar & Irwin, 2010) was developed following careful consideration of the theoretical and empirical research on social selection theory, social causation theory, the life course perspective, and the social production of disease model. Throughout most of the nineteenth century, the belief that disease was a direct result of poverty and undesirable living environments prompted public health efforts focused on improving personal and neighborhood cleanliness (Trattner, 2007). Theoretical advances in thinking about relationships between health and social position reflect an evolutionary process, beginning with the discovery of the germ in the 1870s (Trattner, 2007). In the U.S., 20th century scholarship began with observing trends in relationships between social positions and health (e.g., Britten, 1934; Faris & Dunham, 1939; Knopf, 1914). Later, research efforts turned to the examination of causal pathways (i.e., social selection versus social causation) between social position and health (e.g., Dohrenwend & Dohrenwend, 1967; Dohrenwend et al., 1992; Turner & Wagenfeld, 1967), as well as to identifying health consequences associated with poverty and possible strategies (i.e. reducing poverty or improving healthcare) to improve health for those living in poverty (e.g., Bamberger, 1966; James, 1965). It seems that while theoretical, empirical, and practical discussions supported the existence of relationships between social position/poverty and health, there was not yet agreement on the direction of such relationships, or on whether efforts should be focused on reducing poverty or improving health care.

An important move forward in understanding the social aspects of health came with the publication of the 'Black Report' for the London Department of Health and Social Security, which argued health disparities in the United Kingdom could be reduced if macro interventions were employed in education, housing, and social welfare (Black et al., 1980). This report spurred discussions worldwide, and in 2004 the World Health Organization (WHO) announced the creation of the Commission on Social Determinants of Health, charging it with responsibility for investigating pathways from root causes to health status differences, identifying where and how health inequalities should be addressed, and culminating with the creation of a comprehensive SDOH framework (Marmot, 2005; Solar & Irwin, 2010).

Social selection and social causation theories. Social selection theory and social causation theory have been continuously tested over time, both in isolation, and against each other, to understand relationships between health, social position, and intermediary factors. Social selection theory posits that an individual's health influences their future socioeconomic position (Blane, Smith, & Bartley, 1993; Dunham, 1961). As originally conceptualized, the theory proposed "direct selection," meaning health has a direct impact on future social mobility and socioeconomic position. Social causation theory, however, posited that social position determines health (Turner & Wagenfeld, 1967).

Subsequent research and theoretical discussions have imagined even more complex causal relationships. In the case of social selection theory, research suggested health partially mediates the relationship between prior socioeconomic conditions and life experiences, and future socioeconomic position (Blane et al., 1993). This relationship is referred to as accumulation of disadvantage, and the change in theoretical orientation is termed indirect selection (Blane et al., 1993). Social causation theory evolved to include material (e.g., housing), psychosocial (e.g., social support), behavioral (e.g., smoking, diet), and health system (e.g., insurance status) factors (Solar & Irwin, 2010), through which social position determines health. In the last twenty years, social selection and social causation theories have continued to inform studies regarding social position and health, with the majority of studies indicating support for social causation theory (e.g., Elovainio et al., 2011; Hudson, 2005; Warren, 2009).

Life course perspective. Ideas about the importance of health and social position across the lifespan, and even intergenerationally, were also important in the development of the SDOH framework. The life course perspective describes how SDOH operate at various developmental levels, and across generations, to influence immediate and later health (Solar & Irwin, 2010). This perspective is an additive model in that it further explains social selection and causation theories. Indeed, the placement of direct selection within the life course perspective may have led to the specification of indirect selection within social selection theory. The life course perspective suggests there is an accumulation of risk, in which disease risk or protective factors accumulate over time, and even across generations (Ben-Shlomo & Kuh, 2002). Considerable empirical support exists for the accumulation of risk or protective factors over the lifespan to influence health (Pavalko & Caputo, 2013), but the accumulation may flatten over time and be less applicable in later life (Willson, Shuey, & Elder, 2007).

Social production of disease model. The social production of disease model expanded on the theoretical contributions of social selection and social causation theories and includes the presence of relationships between social stratification and health across time. Diderichsen, Evans, and Whitehead (2001) proposed that social contexts create social stratification, resulting in disparate exposures to conditions that place a person at risk for poor health. Poor health in turn leads to worse social and economic outcomes for the individual, and these individual-level outcomes can also influence societal-level social and economic development. The social production of disease model (Diderichsen et al., 2001) contributed substantially to the Commission on Social Determinants of Health's final framework (Solar & Irwin, 2010).

Final SDOH framework. The varied theoretical mechanisms examined here contributed to the development of the final SDOH framework. The framework depicts bidirectional relationships between socioeconomic and political contexts and socioeconomic position, and taken together these structural determinants (e.g. race, education, gender, sex, and income/poverty) lead to intermediary determinants (e.g., material circumstances, behavioral, biological, psychological, and health system factors), which lead to health and well-being inequity. Individual health and well-being then influence future socioeconomic position and sociopolitical contexts. Given the complex and various pathways depicted in the final SDOH framework, it would be extremely difficult to test in its complete form. Instead, researchers commonly extract various pathways to test smaller portions of the model, including intervening and mediating factors. A vast amount of research has been conducted on the various structural and intermediary determinants of health. As introduced in chapter one, disparities in co-occurring condition rates are present in terms of race, sex, and SES, and disparities in healthcare access and utilization exist for individuals with co-occurring conditions. The SDOH framework can inform inquiries on relationships between social and structural determinants, co-occurring conditions, and social and economic well-being, and is congruent with the social work profession's ecological approach to the social environment and human behavior.

Health as Human Capital Theory

Health economics involves traditional elements found in economics (e.g., supply, demand, and production), but given the nature of health and healthcare, typical economics rules do not apply. For example, health cannot be sold in the capital market (Morris, Devlin, Parkin, & Spencer, 2012), but can be considered a form of human capital that affects future market (i.e., employment) and nonmarket (i.e., household) productivity (Grossman, 1972). Grossman (1972) was the first to construct a model of the demand for health capital, arguing health and knowledge together affect productivity (i.e., employment), including the ability to produce income. Importantly, the model differentiates between health and healthcare and specifies the relationship between them.

Two important concepts key to understanding the economics approach to health are utility and resources. In Grossman's model, utility refers to the decisions individuals make about how to spend their resources (e.g., money and time), based on which choice will provide them with the most personal satisfaction and future income/wealth (Grossman, 2000). Individuals make tradeoffs with their health to maximize perceived utility, even when others perceive it to be contrary to their best interest (Cawley, 2004). An individual's resources are related to utility, as they can affect decisions about utility and tradeoffs of health investments (Grossman, 1972). For example, individual and family income influence access to health insurance, healthcare, healthy foods, and exercise opportunities. Further, the time involved to perform health investments, as well as the amount of time necessary for access (e.g. travel time, distance), are crucial elements of health decision-making. In this way, access is also related to decisions about tradeoffs and utility.

Core components. Individuals produce and demand health: health is produced through health-promoting activities (e.g., exercise, eating a balanced diet, healthcare), and demanded because it increases an individual's ability to participate in market (e.g., employment) and nonmarket (e.g., family) activities. Healthcare, however, is only demanded because it aids in the production of better health (Grossman, 1972). The health as human capital model assumes individuals are born with an initial stock of health that depreciates with age, and increases through investments in healthcare and health-promoting activities, such as nutrient-rich food, abstinence from tobacco and alcohol, and exercise equipment/memberships (Grossman, 1972, 2000; Muurinene & LeGrand, 1985). Importantly, health investments made by individuals always improve health, but the size of the improvement is greater when an individual has poorer health (Grossman, 1972; Morris et al., 2012). Education is also a strong predictor of health, even more so than income and wealth (Grossman & Kaestner, 1997), through increased participation in healthy-lifestyle activities and increased efficiency of the health investments. In terms of efficiency, Grossman (2000) asserted that education can affect perceived utility and tradeoff decisions, translating to individuals being more efficient producers of health. For example, health-promoting activities performed by an individual with more education may result in greater improvements in their health, compared to those with less education. Additionally, people invest in health to increase their productivity (Grossman, 1972). In order for individuals to maximize their productivity, they must maximize the number of healthy days they experience. At the same time, education affects productivity: individuals with higher levels of education are more likely to have active labor force participation, and this relationship may be even stronger for females compared to males (Vecchio et al., 2014). Taken together, Grossman's (1972) model suggests health is improved by participation in health-promoting activities, which can be affected by educational status, and then education and health work in concert to affect productivity.

Theoretical support. Grossman's (1972) model has been used to investigate the economics of physical and mental health and healthcare across a variety of populations within the U.S. and internationally (e.g., Birch et al., 2000; Chirikos & Nestel, 1985; Ettner et al., 1997). The model has also been applied to population health (Mullahy, 2010).

The research authored by Chirikos and Nestel (1985) and Kahn (1998) provide examples of studies that investigated relationships between physical health and employment factors. Chirikos and Nestel (1985) examined the net effects of poor health on wages and annual hours of work using two nationally-representative U.S. surveys: the 1976 National Longitudinal Survey of Older Men and 1977 National Longitudinal Survey of Mature Women. Using two-step regression models, stratified by race and gender, the results indicated having any history of poor health was significantly associated with poor economic outcomes, even among those who experienced health improvements (Chirikos & Nestel, 1985). Differences were also noted by race and gender: Employment activities and earnings of Black participants were more heavily influenced by ever having a health problem, compared to White participants, and the annual earnings of White women were least affected by having any history of poor health (Chirikos & Nestel, 1985). The authors, however, provided few details regarding their sample (e.g., demographics), and it is unclear how individuals were distributed in terms of health status in general and across the race/gender subcategories. Combined with the age of the data, these missing details present limitations for current understanding, but nonetheless this study extends Grossman's (1972) theory with its inclusion of race as an enabling factor in health.

Kahn (1998) investigated employment among adults with reported type-II diabetes between 1976 and 1992, using three nationally-representative cross-sectional datasets: 1976 and 1989 National Health Interview Surveys, and the first wave (1991-1993) of the Health and Retirement Survey. Probit models, controlling for age, BMI, education, race, and marital status, indicated that women with diabetes significantly increased their participation in the workforce (-.36 to -.31, $p<.01$) between 1976 and 1992, however men with diabetes decreased their workforce participation (-.33 to -.47, $p<.01$) over the same time period. Additionally, each year of education increased diabetic women's employment more than it increased non-diabetic women's employment (Kahn, 1998). Changes in education- and employment-related policies and norms between 1976 and 1992 could explain the increased participation of diabetic women in the workforce, which was not accounted for in the models. This study, however, provides support for the prominent inclusion of education in Grossman's (1972) model, highlighting the importance of education for influencing both health and employment.

Grossman's (1972) model has also been applied to mental health. A widely cited study by Ettner et al. (1997) investigated the impact of psychiatric disorders on employment, work hours, and personal income among 4,626 adults (18-54 years of age) in the U.S who completed the National Comorbidity Survey. Controlling for a number of demographic factors (e.g., race/ethnicity, age, rural vs. urban residence, marital status), probit and linear regression model results indicated having any psychiatric disorder significantly reduced employment and conditional annual income for both men and women, and having certain psychiatric disorders was associated with worse outcomes related to income and work hours (Ettner et al., 1997). Women with major depression, agoraphobia, or drug dependence were less likely to work than women without disorders, and for women who did work, agoraphobia, mania, or schizophrenia was associated with lower incomes compared to those with no disorder. For men, major depression or alcohol dependence was associated with lower employment rates, and dysthymia was associated with reduced conditional work hours, compared to men with no disorder (Ettner et al., 1997). No significant relationships were found in terms of work hours for women, or income for men. These statistics on specific psychiatric disorders, however, reflect bivariate relationships due to small cell sizes. This study not only indicated relationships between psychiatric diagnoses and employment outcomes, but also highlighted differences in relationships for men and women.

Another study by Luo et al. (2010) extended beyond diagnosis; the authors constructed instrumental variables to represent the course (i.e., new onset, relapse, remission) of major depression, to examine the effect on labor market outcomes for a nationally-representative sample of U.S. men and women between 18-60 years of age (N = 21,534). The authors used waves one and two of the National Epidemiological Survey of Alcohol and Related Conditions, restricting the sample to only those who reported being employed at wave one, and like Ettner et al. (1997) they also investigated relationships separately by gender. Results of multinomial logistic regression indicated the relationship between the course of major depression and labor market outcomes differed by sex. For example, compared to those with no major depression, men with relapsed major depression were more likely to work part time or be out of the labor force, but women with relapsed major depression were not significantly different from those with no major depression (Luo et al., 2010). Additionally, men with incident depression were more likely to work part time, be unemployed, or be out of the labor force, compared to men without major depression disorder, but for women with incident depression the only significant relationship was with working part time. Luo et al. (2010) did not investigate physical health status specifically but did include the physical component scale of the SF-12 as a covariate, finding significant relationships for both men and women.

One limitation of Grossman's (1972) model is its inability to account for uncertainty. The model assumes individuals have perfect and accurate information about their health, suggesting an individual could even make rational decisions about the circumstance of their death (Morris et al., 2012). Regardless, the model is commonly applied in economics research on the production of health and productivity, and is being increasingly used to examine health inequalities (Morris et al., 2012). Grossman's (1972) model was also limited in its inclusion of structural determinants that affect health. Extensions of the model have addressed this limitation through the inclusion of additional structural factors, such as race, sex, and SES, as enabling factors in the production of health (e.g., Chirikos & Nestel, 1985; Gaskin & Roberts, 2012; Kahn, 1998; Luo et al., 2010).

Gaskin and Roberts (2012) extended Grossman's (1972) model to examine the effects of social class on health. The authors constructed a conceptual framework that suggests that poverty limits demand for healthcare services and health-promoting lifestyle factors, and in turn, the lower consumption of healthcare and lifestyle factors reduces health status and in effect increases need for healthcare (i.e., derived demand). Logistic regression was used to test their conceptual model on health care utilization using the 2006 Medical Expenditures Panel Study (MEPS; N = 23,24), finding that health status declined with poverty status. Poor adults (less than 100% FPL) had the lowest self-reported health status and the lowest functional status, but also had lower utilization of healthcare services compared to affluent adults: Poor and near-poor (100-125% FPL) adults were less likely to use 14 of 16 services; exceptions were hospital stays and ER visits (Gaskin & Roberts, 2012). Additionally, adults with a high school diploma or a lesser degree of education were less likely to use most types of healthcare services compared to those with a college degree, uninsured nonelderly adults were less likely to use services than privately insured non-elderly adults, and adults with Medicaid were less likely to use some healthcare services, compared to privately-insured adults (Gaskin & Roberts, 2012). This study provides support for the inclusion of SES, education, and health insurance status as enabling factors for healthcare utilization.

Arendt (2012) further examined health insurance as an enabling factor for healthcare utilization among individuals living in Denmark, a country with a universal healthcare system. Denmark's system, however, still yields unequal access to healthcare, as higher-SES individuals can purchase supplemental private insurance. Results indicated that while all individuals had access to universal healthcare, low-SES individuals had lower utilization of general practice, hospitalization, specialist care, and dental care, compared to the higher-SES groups (Arendt, 2012). These results, and the healthcare system, are relevant to the study of individuals with co-occurring conditions, given that many individuals with SMI have access to subsidized health insurance through Medicaid, but may still be required to participate in cost sharing to access healthcare and medications (Powell, Saloner, & Sabik, 2016). Further, Medicaid's low reimbursement rates act as a deterrent for many healthcare providers, limiting the supply of providers and thus presenting another barrier for recipients (Gaskin & Roberts, 2012). Consequently, even if an individual with SMI has access to subsidized healthcare through Medicaid, health insurance may still have a mediating role between demographic and socioeconomic enabling factors, and health. Medicaid may also promote health-related tradeoffs that differ from individuals without access to Medicaid so that recipients may focus their resources on formal healthcare services rather than on lifestyle factors such as healthy food and exercise (Gaskin & Roberts, 2012).

Summary. Taken together, this research provides support for the relationships between health and labor market outcomes (e.g., employment, income/wage, work hours) described in the health as human capital model, across a variety of populations. Additionally, these studies demonstrate the model's evolution to include SDOH in empirical analyses, and its application to healthcare systems that include subsidized healthcare for some or all of the population. The health as human capital model has been used to investigate mental or physical health problems separately, and it is feasible to apply the model to investigate employment outcomes for individuals with co-occurring conditions. Individuals with mental health conditions experience an increased prevalence of physical health conditions (e.g., Lee et al., 2015; Razzano et al., 2015), and these co-occurring conditions are associated with disparities in healthcare utilization (e.g., Shen et al., 2008). Given this, Grossman's (1972) model can be used to examine relationships between healthcare utilization, health, and employment for individuals with co-occurring conditions.

Behavioral Model for Health Service Utilization

Also important to the study of relationships between healthcare utilization, health, and employment for individuals with co-occurring conditions, is the behavioral model for health service utilization (Andersen, 1995; Andersen & Newman, 1973). While this model is not the focus of this dissertation, its contributions clarify the structural mechanisms that influence healthcare utilization. The original model reflected a causal relationship between predisposing factors (i.e. demographic, social structure, health beliefs), enabling factors (i.e., family income and resources, community resources and healthcare costs), illness level (i.e., perceived and objective), and healthcare utilization (Andersen & Newman, 1973). Over time, the model has evolved to include external health system factors more deliberately, broader definitions of each factor category, and individual health behaviors in addition to health service utilization (Andersen, 1995). Additionally, perceived health status, objective health indicators, and consumer satisfaction were added to the model as long-range outcomes (Andersen, 1995). Congruent with the SDOH framework and Grossman's (1972) model, the behavioral model for health service utilization demonstrates the importance of sex, age, SES, race, and ethnicity in influencing healthcare access, and the importance of healthcare access to improve utilization and future health (Andersen, 1995; Andersen & Newman, 1973).

The behavioral model for health service utilization has been used in research that examines healthcare utilization for individuals with co-occurring conditions. Lee et al. (2015) drew on the behavioral model of health service utilization to advance understanding of the relationship between co-occurring conditions and healthcare expenditures. Using nationally-representative data from the 2011 MEPS, the authors compared the interaction effect of SMI and physical health conditions for adults 18-64 years of age ($N=17,764$). The authors found the presence of SMI ($b=.97$, $p<.001$), and the interaction of mental and physical health conditions ($b= -.23$, $p<.001$), were significant predictors for healthcare expenditures. Unexpectedly, however, the results suggested that the effect of having additional physical health conditions on total healthcare expenditures were *smaller* for those with SMI. Specifically, those with SMI experienced a 17.4% increase in healthcare expenditures for each physical health condition, but those without SMI experienced an increase of 44.8% for each physical health condition. The authors surmised that healthcare access and utilization differed for those with SMI beyond the predisposing, enabling, and need factors examined (Lee et al., 2015). Given the connection between healthcare utilization and healthcare expenditures, differences in utilization patterns could explain the unexpected result in terms of healthcare expenditures.

Healthcare Utilization for Adults with Co-Occurring Conditions

Research examining healthcare utilization patterns for adults with SMI includes broad groups of individuals with mental health conditions (Dickerson et al., 2003; Shen et al., 2008), and individuals with specific mental and/or physical health diagnoses (Egede, 2007; Sullivan, Han, Moore, & Kotrla, 2006). While the authors did not include physical health diagnoses in their study, Dickerson et al. (2003) was among the first to examine physical health care utilization among people with SMI. The authors surveyed 200 adults with SMI at two community mental health centers and made comparisons to matched samples from three nationally-representative surveys of persons without mental health conditions. Controlling for age, race, and gender, logistic regression results indicated individuals with affective disorders were more likely to visit a general medical doctor (OR=2.37), consult a medical specialist (OR=2.41), and have more emergency room visits for medical problems (OR=3.21), in the prior year, compared to those without SMI. Individuals with schizophrenia were also more likely to visit a general medical doctor in the past year (OR=2.04), compared to those without SMI. Significant differences between the SMI groups and comparison group were also noted in terms of specific physical healthcare activities (e.g., blood pressure screenings, receive flu shot). Interestingly, the only significant differences in utilization between the SMI groups were in complementary and alternative medicine use. A primary limitation of this study is the use of a small sample of individuals with SMI, and the sampling methodology was only vaguely described. While an even number of individuals with each mental health condition was included (n=50), it is unclear how these individuals were selected.

Reducing study limitations due to sampling, Shen et al. (2008) and Egede (2007) examined healthcare utilization using nationally-representative individuals. Shen et al. (2008) used the MEPS (N = 2440) to investigate the relationship between co-occurring mental illness (defined broadly to include affective disorders, anxiety, somatoform disorders, dissociative and personality disorders, and schizophrenia) and healthcare utilization for obese adults (body mass index over 30) with chronic physical health illness (reported diagnosis of asthma, diabetes, heart disease, HTN, or osteoarthritis). Bivariate chi-square results indicated participants with mental health conditions were more likely to use inpatient, emergency room, and other healthcare services; however multivariate logistic regression controlling for demographic and health-related factors only found a significant relationship for emergency room use (OR=1.41, $p<.01$). Egede (2007) investigated healthcare utilization for adults with and without chronic physical health diagnoses, and major depression, using data from the National Health Interview Survey (N = 30,801). Multivariate logistic regression (controlling for demographic and health-related factors) indicated individuals with co-occurring major depression and chronic physical health conditions were more likely to have one or more ambulatory visits (OR=1.73, $p<.05$) and one or more emergency department visits (OR=1.94, $p<.05$), compared to those without either condition. Additionally, the odds ratios for both outcomes were greater for those with co-occurring conditions, compared to those with chronic physical health conditions only, but it is not possible to infer whether the difference is statically significant as it was not examined. Thus, Egede's study was not able to examine whether the added burden of depression mediates the relationship between chronic physical health conditions and healthcare utilization.

Sullivan and colleagues (2006) examined diabetes-related hospitalizations for individuals with mental health conditions. The authors used administrative data from a single hospital between 1994 and 1998 to examine disparities in hospitalization rates following visits to the emergency department, for those with a primary diagnosis of schizophrenia, bipolar, depression, or anxiety, or no such mental health condition (N = 4,275). Controlling for age, gender, race, time of arrival, and mode of arrival, results indicated individuals with psychotic (OR=.77) and nonpsychotic (OR=.55) mental health conditions were significantly less likely to be admitted to the hospital for a diabetes-related reason, following a visit to the emergency department. Paired with findings that suggest individuals with mental health conditions are more likely to visit the emergency room than those without mental health conditions (Egede, 2007; Shen et al., 2008), these findings suggest that individuals may be utilizing the emergency department for reasons that do not require hospital admission. However, research is needed to support this hypothesis.

Summary of healthcare utilization research. Research on healthcare utilization patterns for individuals with co-occurring conditions is limited, however available research suggests individuals with SMI have higher utilization rates of outpatient and emergency healthcare services (Dickerson et al., 2003), but lower likelihood for inpatient hospitalization (Sullivan et al., 2006). Findings related to healthcare utilization patterns for individuals with co-occurring conditions are not consistent: while Egede (2007) found higher utilization in a multivariate context, Shen et al. (2008) only found a relationship in bivariate analyses. The differing sampling and measurement designs of these studies make it difficult to make generalized statements regarding healthcare utilization among individuals with co-occurring conditions. Of particular note, no study was identified that examined healthcare utilization among adults with SMI and a co-occurring physical health condition, compared to those with SMI only. Only two studies used nationally-representative data and these studies either limited the sample to a single SMI diagnosis or had an additional sample restriction regarding BMI.

There is a need for nationally representative research that examines healthcare utilization for individuals with co-occurring conditions that includes a broader definition of SMI, fewer physical health restrictions, and SMI-only as the comparison group.

Health-Related Quality of Life

Definition and overview. HRQOL is a multidimensional construct focused on an individual's perceptions of their health-related physical, mental, emotional, and social functioning (Centers for Disease Control and Prevention, 2016; Office of Disease Prevention and Health Promotion, 2017). HRQOL is the preferred health status variable for economic analysis in developed countries, including the U.S (e.g., Currie & Madrian, 1999), and it is commonly used in social and behavioral science research (e.g., Calvert, Isaac, & Johnson, 2012; Carlozzi & Tulsky, 2013; Neely-Barnes, Graff, & Washington, 2010). The non-reductionist nature of HRQOL is congruent with social work values (National Association of Social Workers, 2008), in that it values an individual's perceptions of their health and functioning. While objective measures of health (e.g., weight, lab results, health diagnoses and screenings) are valuable, HRQOL provides additional information about an individual's health, offering a more comprehensive assessment of health. HRQOL, however, is related to objective health indicators. Research has consistently indicated that many mental and physical health diagnoses are associated with worse HRQOL, and HRQOL worsens as the number of chronic health conditions increases (e.g., Agborsangaya, Lau, Lahtinen, Cooke, & Johnson, 2013; Porensky et al., 2009; Singh et al., 2005).

Several measures of HRQOL are available for use in quantitative research, including both general and disease/condition-specific measures (Morris et al., 2012). Two commonly used measures for general HRQOL include the EuroQol-5D (EQ-5D), and the Medical Outcomes

Study Short Form-36 (SF-36) and its even shorter forms, the SF-12 and SF-6. The focus here is on the SF measures, which include two distinct components of HRQOL (physical and mental) measured by 36, 12 or six items (depending on the version used). To include these components as manifest variables in statistical analyses, individual item scores can be summed to provide overall scores that indicate an individual's physical and mental HRQOL (Ware, Kosinski, & Keller, 1996). The SF-36 additionally provides scores for nine subcomponents of HRQOL (Ware & Gandek, 1998).

Differences in demographic and structural factors have been noted in regards to HRQOL. This study uses the SF-12 as a measure of HRQOL; thus differences in regard to the SF-12 will be highlighted. Fleishman & Lawrence (2003), conducted an in-depth measurement study to investigate demographic variations in scores on the SF-12 among the general U.S. population. Results of their study indicated that women tend to have lower mean HRQOL scores compared to men, and individuals with no high school degree, or a high school degree only, have lower HRQOL scores compared to those with higher levels of education (Fleishman & Lawrence, 2003). Age is also related to HRQOL, but the relationship varies depending on the component of HRQOL considered: physical HRQOL tends to decrease as an individual gets older, but mental HRQOL increases (Fleishman & Lawrence, 2003). The authors did not find any strong racial and ethnic differences in HRQOL scores.

Results for adults with SMI have basically replicated these patterns, with some interesting differences noted. Salyers, Bosworth, Swanson, Lamb-Pagone, & Osher (2000) and Chum, Skosireva, Tobon, & Hwang (2016) found no statistically significant differences in terms of sex (i.e., male or female) for physical component scores (PCS) or mental component scores (MCS) in samples of adults with SMI in the U.S and Canada. Salyers et al. (2000) also found no increase in MCS scores for older versus younger adults with SMI in the U.S. (N=946), and found a statistically significant difference in MCS scores for Black or other race adults with SMI, compared to White adults with SMI (Salyers et al., 2000). In a sample of 574 homeless adults with SMI in Canada, however, Chum et al. (2016) observed the expected increase in MCS among older participants, and also observed no differences for ethnic or racially-diverse diverse participants. Chum et al. (2016) also examined differences in PCS or MCS by educational attainment, however the authors found that while participants with less than a high school education had lower PCS compared to those with a high school education, participants with some post-secondary education had PCS almost identical to those without a high school education. No significant differences in MCS were noted for study participants (Chum et al., 2016). It is possible that relationships between demographic/structural factors and HRQOL may exist for individuals with SMI, compared to the general population. However, given limited research in the area, additional research is warranted to examine relationships between social determinants and HRQOL.

Healthcare utilization and HRQOL. While healthcare utilization and HRQOL are commonly investigated within the same study, they are often examined separately as important health-related outcomes (e.g., Agborsangaya et al., 2013; Porensky et al., 2009; Singh & Strand, 2008; Williams et al., 2012). Some research has examined HRQOL as a predictor for healthcare utilization. For example, Singh et al. (2005) investigated healthcare utilization and HRQOL among veterans in the U.S. (N = 40,508). The authors completed bivariate analyses regarding HRQOL, finding that diagnoses of arthritis, COPD, depression, diabetes, HTN, and a heart condition were each associated with decreased scores in mental and physical HRQOL. Additionally, multivariate analysis indicated that physical and mental HRQOL, as measured with manifest component scores derived from the SF-36, were associated with increased odds of inpatient, primary care, specialty medicine, and surgical utilization (Singh et al., 2005). While the authors controlled for healthcare utilization 12 months prior, cross-sectional data was used, making it difficult to evaluate the direction of these relationships. Another study of physical HRQOL, measured with a manifest component score from the SF-12, and healthcare utilization by Chamberlain et al. (2014) included heart failure patients (N = 417). Results similarly indicated that poor HRQOL was associated with increased hospitalization and emergency room utilization, but no significant relationship was found with outpatient utilization. Sandberg, Kristensson, Midlöv, Fagerström, and Jakobsson (2012) also found that physical HRQOL predicted total number of hospital stays and total hospitalization lengths of stay, in a sample of Swedish individuals 60 years of age and older (N = 1402).

The relationship between healthcare utilization and HRQOL is complex. Lower levels of HRQOL are indicative of poorer health, and often are associated with individuals utilizing more healthcare. For example, Salyers et al. (2000) found that among adults with SMI, those with two or more health visits in the past six months, or one or more hospitalization day in the past six months, had lower physical and mental HRQOL scores. Such a relationship is theoretically supported by the behavioral model for healthcare utilization (Andersen, 1995; Andersen & Newman, 1973); but at the same time, theory also suggests healthcare utilization improves health (Andersen, 1995; Grossman, 1972, 2000). Available research appears to support the behavioral model for healthcare utilization in that it suggests a negative relationship between HRQOL and healthcare utilization: worse health is associated with increased healthcare utilization (e.g., Chamberlain et al., 2014; Sandberg et al., 2012; Singh et al., 2005). However, there is a lack of research that examines healthcare utilization as a predictor for improved HRQOL, making this an important gap in the literature that warrants empirical investigation.

HRQOL and employment. Research indicates statistical relationships between HRQOL and employment. Many studies have examined mean-differences in HRQOL scores by employment status (e.g., Banks & Lawrence, 2006; Miller & Dishon, 2006; Worthington & Krentz, 2005), and employment status as a predictor for HRQOL in regression models (e.g., Miller & Dishon, 2006; Worthington & Krentz, 2005). It is not surprising that employment is associated with better HRQOL, given the relationship between employment and SES, and established relationships between health and employment (Grossman, 1972, 2000), which may indicate employed persons enjoy a better health status. In an article reporting on a systematic review of employment and HRQOL for individuals with schizophrenia, Bouwmans, de Sonneville, Mulder, & Hakkaart-van Roijen (2015) noted the difficulty of interpreting the direction of the relationship between HRQOL and employment, pointing out that while theory suggests HRQOL improves employment there is a dearth of literature that explores such a causal pathway for individuals with schizophrenia.

Given the research on health and employment, it is surprising that few studies have examined HRQOL as a predictor for employment outcomes. Murphy, Tubridy, Kevelighan, and O'Riordan (2013) investigated HRQOL as a predictor for employment, examining relationships between HRQOL and time to loss of employment among Irish individuals with Parkinson's Disease (N = 88). The authors found that higher scores on the vitality subcategory of the SF-36 were associated with prolonged employment following diagnosis. In regard to SMI, only one study was located that examined the relationship between employment and HRQOL. Simon, Ludman, Unützer, Operskalski, & Bauer (2008) examined relationships between mood symptoms and work productivity for persons with bipolar disorder (N = 412). Included in their study was an analysis of relationships between HRQOL and employment. HRQOL was measured with two selected subscales of the SF-36: social role function and role-emotional. Bivariate t-tests indicated that individuals with bipolar disorder who were employed had higher mean scores on both subscales of the SF-36 (social role function score: $t=2.88$, $p<.01$; role-emotional score: $t=3.90$, $p<.001$). The lack of research that examines HRQOL as a predictor for employment results in a significant gap in the literature, calling into question the causal relationship between the two factors.

Summary of HRQOL research. HRQOL is a multidimensional construct representing individual health (Centers for Disease Control and Prevention, 2016; Office of Disease Prevention and Health Promotion, 2017). Research suggests that many mental and physical health diagnoses are associated with lower levels of HRQOL (e.g., Agborsangaya et al., 2013; Porensky et al., 2009; Singh et al., 2005), and that for individuals with SMI, co-occurring physical health conditions are associated with lower levels of HRQOL (Salyers, et al., 2000). Available literature on HRQOL for individuals with SMI, however, has included samples of participants from selected sites and states, and has examined bivariate relationships. No literature on HRQOL for adults with SMI and co-occurring physical health conditions is available that uses a national U.S. sampling frame. Thus, there is a need for a nationally-representative study that examines these potential differences in a multivariate context. Available research suggests that low HRQOL is predictive of increased healthcare utilization (e.g., Chamberlain et al., 2014; Sandberg et al., 2012; Singh et al., 2005), providing support for the behavioral model for healthcare utilization (Andersen, 1995; Andersen & Newman, 1973), but there is a shortage of literature that examines whether healthcare utilization improves an individual's HRQOL. While limited in number, research also suggests that HRQOL is related to employment (Murphy et al., 2013; Simon et al., 2008). Grossman (1972, 2000) suggests that healthcare utilization improves health, and individual health is related to an individual's employment. There is a need to examine HRQOL among individuals with co-occurring conditions, as well as the relationships between healthcare utilization, HRQOL and employment for this population.

Employment and Co-Occurring Conditions

Given that employment is a key outcome for persons with SMI, there is a large and varied body of research from which to draw insights. Research on employment for individuals with SMI has primarily focused on clinical indicators (e.g. psychiatric hospitalization, symptomology, and substance abuse), medication, cognitive functioning, and education (e.g., Ellinson et al., 2007; Luciano & Meara, 2014; Luo et al., 2010). In fact, only six studies on employment for individuals with SMI were located that included physical health in any way. Among these was the study by Egede (2007) discussed in the previous section. While Egede's study did not explicitly focus on employment, the study included an analysis of the relationship between lost workdays due to illness and chronic condition status. Results indicated no significant relationship between co-occurring conditions and the number of lost workdays due to illness. Importantly, it is likely that only those individuals who reported employment were asked this question as part of the survey due to inherent skip patterns. Additionally, the variable was categorized to reflect a response of 'none' or 'one or more'. Given that it is common for individuals to miss a day of work due to illness, the categorization of the variable in this way may minimize the effect of co-occurring depression and physical health conditions.

Ammerman and colleagues (2016) also used a nationally-representative sample to examine employment and labor productivity costs associated with depression among high-risk, low income mothers who completed the MEPS between 1996 and 2011 (N=20,531). Physical health comorbidities were included as covariates in models examining relationships between depression and employment outcomes. Thus, interpretations of results associated with physical health conditions are for the entire sample. Multivariate results, controlling for race, age, number of children, health status, selected health diagnoses, education, employment characteristics, census region and year of MEPS completion, indicated depression was associated with missing any work days (OR=1.40, p<.01), but not the probability of unemployment or number of missed work days. Using these models, the authors also estimated the expected annual indirect cost of depression on labor productivity costs to be $457 per person. However, given that depression was not a statistically significant predictor for probability of employment and number of missed workdays, the significance and meaning of this calculation is questionable.

As discussed previously, relationships between mood symptoms and work productivity for persons with bipolar disorder (N = 412) were studied by Simon et al. (2008). In addition to including a measure for HRQOL, the authors also included medical comorbidity (RxRisk score, based on pharmacy data) in a longitudinal pre-post study. Medical comorbidity, however, was not included in the primary logistic and linear regression models, instead the authors focused on mood symptomology (i.e., depression, mania) as a predictor for employment outcomes. Results from a bivariate t-test indicated individuals who were employed at baseline did not significantly differ on mean RxRisk score (t=1.54, p=.12). These results are limited by the chosen statistical method and the chosen measurement for medical comorbidity. Medical comorbidities were assessed using RxRisk scores, based on prescriptions that were filled by participants six months prior to enrollment in the study. Given this, the measure only represents medical comorbidity for participants who were treated for a medical condition with prescription medication in the six months prior to enrollment. Participants diagnosed with a condition but not taking medication during this time period, for whatever reason, would not be accounted for using this method.

Three studies that examined relationships between co-occurring conditions and employment outcomes were conducted outside the U.S. Two studies examined employment-related characteristics for individuals with bipolar disorder in Canada (McIntyre et al., 2006; Ruzickova et al., 2003), and a third examined the relationship between depression, diabetes, and lost productivity in Hungary (Vamos, Mucsi, Keszei, Kopp, & Novak, 2009). McIntyre et al. (2006) used the Canada Community Health Survey, a nationally-representative survey, restricted to those who reported having at least one manic episode in their lifetime ($N = 938$). The majority of the sample reported at least one chronic physical health condition ($n = 622$). Results indicated that a co-occurring chronic physical health condition was associated with being permanently unable to work (37.5% vs. 17.4%, $p<.05$), having low income (16.8% vs. 10.8%, $p<.05$), and having their main source of income be from social assistance/welfare (9.7% vs. 3.6%, $p<.05$). Another Canadian study by Ruzickova et al. (2003) utilized the Maritime Bipolar Registry, which included individuals 15 to 82 years of age with a confirmed bipolar disorder diagnosis ($N=222$). Employment was not the primary purpose of this study, however disability receipt was included to describe the sample and analyze between-group differences. Only twenty-six participants had co-occurring bipolar disorder and diabetes. Chi-square results indicated individuals with bipolar disorder that had a co-occurring diagnosis of diabetes were more likely to receive long-term disability (81% vs. 30%, $p<.001$).

Vamos et al. (2009) examined the relationship between depression, diabetes, and lost productivity among a representative sample of Hungarian individuals (N=12,643). Individuals with co-occurring diabetes and depression (n=218) had higher numbers of bed days (86.8) and lost work days (78.5) compared to those without diabetes or depression. Multinomial logistic regression was performed, controlling for demographics and health characteristics, to examine whether the presence of diabetes alone, or co-occurring diabetes and depression, increased the likelihood an individual would report a number of bed days or lost work days that was higher than the sample mean. Results indicated individuals with co-occurring depression and diabetes had higher odds of 10 or more lost workdays due to illness ($OR=3.3$, $p<.05$), and 20 or more bed days ($OR=2.7$, $p<.001$), compared to individuals with neither diabetes nor depression.

Summary of employment research for co-occurring conditions. Available research provides little insight about the relationships between co-occurring conditions and employment outcomes, including the cumulative effect of co-occurring conditions on employment status, employment productivity, and employment stability, as well as modifiable mediating factors between diagnoses and employment outcomes (e.g., healthcare receipt). Given a heightened interest in healthcare access following the passing of the ACA (2010), it is important to consider whether healthcare receipt improves health and employment for individuals with co-occurring conditions. Available research on employment for individuals with co-occurring conditions is limited by methodology and sample location. Half of the studies were conducted outside of the U.S. and may not be applicable to the U.S. population with regard to healthcare and employment policy and associated SDOH. Additionally, many of the studies used bivariate analyses and/or included physical health only as a covariate where mental health was the primary variable of interest. Also, all studies included only physical health diagnoses, and did not consider mediating variables between diagnosis and employment, such as healthcare receipt and HRQOL.

Overall Summary and Critique of the Literature

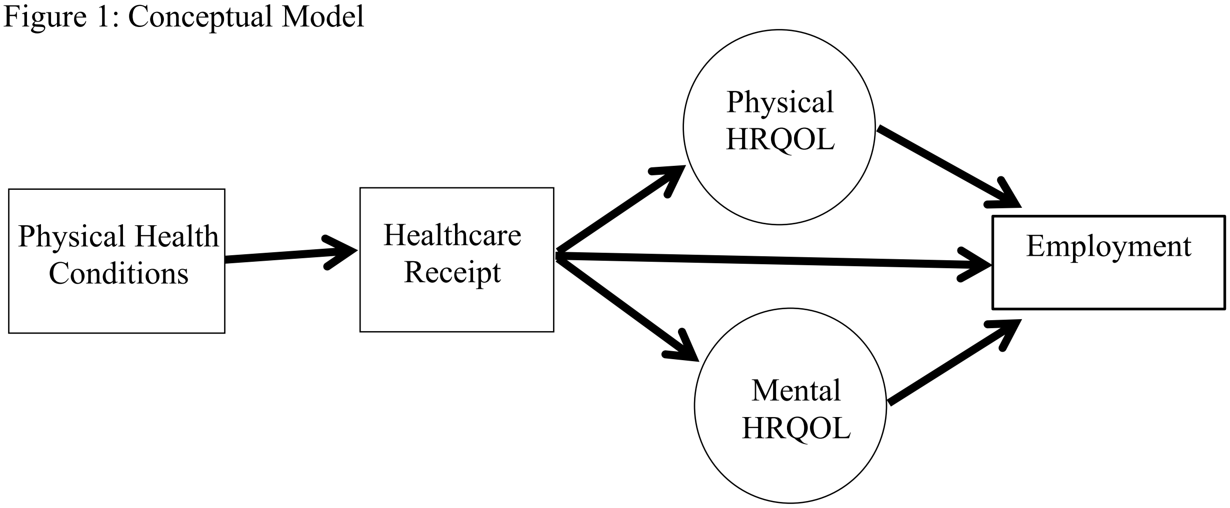
Theoretical models provide support for a relationship between health, healthcare, and employment for individuals with co-occurring mental and physical health conditions. Grossman's (1972) health as human capital model for the production of health and employment suggests that healthcare may improve health and employment outcomes for persons with co-occurring conditions. Empirical research provides support for the health as human capital model among samples of individuals with mental or physical health conditions (e.g., Birch et al., 2000; Chirikos & Nestel, 1985; Ettner et al., 1997), and there is the opportunity to apply the model to investigate employment outcomes for individuals with co-occurring mental and physical health conditions. At the same time, the social determinants of health (SDOH) framework (Solar & Irwin, 2010) describes mechanisms by which structural factors such as race, sex, and SES influence individuals' health and socioeconomic position, and the behavioral model of health service utilization (Andersen, 1995; Andersen & Newman, 1973) describes relationships between healthcare service need, access, and utilization.

Empirical research suggests individuals with SMI experience elevated rates for many chronic physical health conditions, as well as for multiple chronic physical health conditions (e.g., Lee et al., 2016; Lee et al., 2015; Razzano et al., 2015). Risk for co-occurring conditions is also elevated for individuals with SMI who are female, Black/African American, Hispanic/Latino, or of low SES (e.g., Cabassa et al., 2013; McEvoy et al., 2005; Ortega et al., 2006; Razzano et al., 2015). While the available research is limited in many respects, individuals with co-occurring conditions have disparate utilization of healthcare services (e.g., Dickerson et al., 2003; Shen et al., 2008; Sullivan et al., 2006) and poor employment outcomes (e.g., Egede, 2007; McIntyre et al., 2006; Simon et al., 2008). Further, research suggests that HRQOL is related to healthcare utilization (e.g., Chamberlain et al., 2014; Sandberg et al., 2012; Singh et al., 2005) and employment (e.g., Banks & Lawrence, 2006; Murphy et al., 2013), including for individuals with SMI (Simon et al., 2008). Gaps in the available literature demonstrate a need for research that examines healthcare utilization and HRQOL for individuals with co-occurring conditions, and whether receipt of healthcare produces better HRQOL, and in turn better employment outcomes, for individuals with co-occurring conditions.

Chapter 3: Methodology

The health as human capital model (Grossman, 1972) suggests that healthcare may improve health and employment outcomes for persons with co-occurring conditions. Further, empirical research suggests these individuals have higher utilization of healthcare services, however no known research has examined whether receipt of healthcare produces better health, and in turn better employment outcomes, for adults with co-occurring physical and mental conditions. At the same time, structural determinants such as race, sex, and SES influence individual health, and research indicates the presence of disparities in co-occurring condition rates based on these social determinants. The SDOH framework (Solar & Irwin, 2010), the behavioral model for healthcare utilization (Andersen, 1995; Andersen & Newman, 1973), and the health as human capital model (Grossman, 1972) together provide a research framework to examine healthcare utilization, HRQOL, and employment outcomes for individuals with co-occurring conditions. The following conceptual model is proposed (see figure 1).

Figure 1: Conceptual Model



Research Questions and Hypotheses

This study examined six research questions regarding health conditions, healthcare, HRQOL, and employment for individuals with SMI.

1. What are the differences in healthcare receipt for individuals with co-occurring physical health conditions, compared to individuals with SMI only?
   a. Hypothesis 1: Individuals with co-occurring physical health conditions will report higher healthcare receipt compared to individuals with SMI only.
2. What are the differences in HRQOL for individuals with co-occurring physical health conditions, compared to individuals with SMI only?
   a. Hypothesis 2.1: Individuals with co-occurring physical health conditions will report lower physical HRQOL compared to individuals with SMI only.
   b. Hypothesis 2.2: Individuals with co-occurring physical health conditions will report lower mental HRQOL compared to individuals with SMI only.
3. What are the differences in employment status and missed days of work due to illness for individuals with co-occurring physical health conditions, compared to individuals with SMI only?
   a. Hypothesis 3.1: Individuals with co-occurring physical health conditions will report lower rates of employment compared to individuals with SMI only.
   b. Hypothesis 3.2: Employed individuals with co-occurring physical health conditions will report more missed days of work compared to individuals with SMI only.
4. What are the direct relationships between healthcare receipt, physical HRQOL, mental HRQOL, and employment, for individuals with SMI?
   a. Hypothesis 4.1: Healthcare receipt will have a positive relationship with physical HRQOL.
   b. Hypothesis 4.2: Healthcare receipt will have a positive relationship with mental HRQOL.

c. Hypothesis 4.3: Healthcare receipt will have a positive relationship with employment.
d. Hypothesis 4.4: Physical HRQOL will have a positive relationship with employment.
e. Hypothesis 4.5: Mental HRQOL will have a positive relationship with employment.

5. Do healthcare receipt, physical HRQOL, and mental HRQOL mediate relationships between the presence of a chronic physical health condition and employment, for individuals with SMI?
   a. Hypothesis 5.1: Healthcare receipt will mediate the relationship between the presence of a chronic physical health condition and physical HRQOL.
   b. Hypothesis 5.2: Healthcare receipt will mediate the relationship between the presence of a chronic physical health condition and mental HRQOL.
   c. Hypothesis 5.3: Physical HRQOL will mediate the relationship between presence of a physical health condition and employment.
   d. Hypothesis 5.4: Mental HRQOL will mediate the relationship between presence of a physical health condition and employment.
   e. Hypothesis 5.5: Physical HRQOL will mediate the relationship between healthcare receipt and employment.
   f. Hypothesis 5.6: Mental HRQOL will mediate the relationship between healthcare receipt and employment.
   g. Hypothesis 5.7: Healthcare receipt and physical HRQOL will together mediate the relationship between the presence of a chronic physical health condition and employment.

h. Hypothesis 5.8: Healthcare receipt and mental HRQOL will together mediate the relationship between the presence of a chronic physical health condition and employment.

6. Do healthcare receipt, physical HRQOL, and mental HRQOL mediate relationships between number of chronic physical health conditions and employment, for individuals with SMI?
    a. Hypothesis 6.1: Healthcare receipt will mediate the relationship between number of chronic physical health conditions and physical HRQOL.
    b. Hypothesis 6.2: Healthcare receipt will mediate the relationship between number of chronic physical health conditions and mental HRQOL.
    c. Hypothesis 6.3: Physical HRQOL will mediate the relationship between number of physical health conditions and employment.
    d. Hypothesis 6.4: Mental HRQOL will mediate the relationship between number of physical health conditions and employment.
    e. Hypothesis 6.5: Physical HRQOL will mediate the relationship between healthcare receipt and employment.
    f. Hypothesis 6.6: Mental HRQOL will mediate the relationship between healthcare receipt and employment.
    g. Hypothesis 6.7: Healthcare receipt and physical HRQOL will together mediate the relationship between number of chronic physical health conditions and employment.
    h. Hypothesis 6.8: Healthcare receipt and mental HRQOL will together mediate the relationship between number of chronic physical health conditions and employment.

Data Source

This study used secondary data from the panels 17, 18, and 19 of the Medical Expenditures Panel Survey (MEPS). The MEPS is a large nationally representative survey, conducted annually by the Agency for Healthcare Research and Quality (AHRQ) since 1996, with U.S. families and medical providers (AHRQ, 2009). The sampling frame for the MEPS includes participants from the prior year's National Health Interview Survey who completed data collection during the first or last quarters of the year. The National Health Interview Survey uses a stratified multistage probability sampling design, and oversamples households containing Black, Hispanic, and Asian individuals, or those with a family income less than 200% of the Federal poverty level (AHRQ, 2008). The MEPS maintains the oversampling procedures performed by the National Health Interview Survey, and accounts for them in supplied survey weights. Panels 17, 18, and 19 included data collected between 2012 and 2015. Specifically, data were collected from panel 17 participants between the first quarter of 2012 and the last quarter of 2013, panel 18 data were collected between the first quarter of 2013 and the last quarter of 2014, and panel 19 data were collected between the first quarter of 2014 and the last quarter of 2015 (AHRQ, n.d.).

This study used the household component of the MEPS survey, which collects demographic, health, medical service, medical costs/payments, healthcare access and satisfaction, health insurance, income, and employment information from individuals and families at five data collection points over a two-year period. The MEPS is a desirable data source due to its design and focus. The panel design of the MEPS allows for temporal ordering among the variables included in the model and the survey collects a plethora of information on health, healthcare, and employment.

Data were collected using computer assisted personal interviewing (CAPI), which employs computer software to presents the questionnaire on computer screens to each interviewer (AHRQ, n.d.). CAPI guides the interviewer through the questionnaire, automatically routing the interviewer to appropriate questions based on answers to previous questions. Additionally, after interviewers enter survey responses into the computer, the CAPI program ensures the response is within the allowable range, checks for consistency against other collected data, and then saves the responses into a survey data file. Supplemental data was also collected via mailed paper-questionnaires. In addition to data collected from CAPI, data from the mailed Adult Supplemental Questionnaire, sent to all adults 18 years of age or older during rounds 2 and 4, were also used for this study.

MEPS data are contained within panel-specific longitudinal data files, as well as separate ‘medical conditions’ files that list all medical diagnoses reported by a household participant. The medical conditions files are provided in ‘long’ format, with multiple rows for each household member to provide specific information about each reported medical condition. To prepare the data for analysis, the ‘medical conditions’ files were reshaped into wide format, and then merged with the longitudinal files using the DUPERSID unique identifier variable, according to instructions provided by AHRQ (2014, 2015, 2016, 2017). Finally, the three separate longitudinal data files from each of the panels of data were merged together for a complete dataset.

Sample

The sample for this study included adults between 18 and 70 years of age who reported a SMI diagnosis (N=648). The full retirement age in the U.S. ranges between 65 and 67, depending on when an individual was born (Social Security Administration, n.d.). However, some individuals retire early, while others may need to work beyond the typical retirement age due to low wealth or insufficient/absent retirement benefits. Individuals over the age of 70 were excluded from the sample to minimize sample selection bias due to individuals being categorized as unemployed when they have left the labor force due to retirement and have no intent to return. The presence of SMI was measured using the ICD-9 codes 295, 296, and 298 (AHRQ, 2014, 2015, 2016, 2017). These codes represent diagnoses of major depressive disorder, bipolar disorder, schizophrenia, and other psychotic disorder/psychosis. This procedure for measuring SMI was similarly used by Lee et al. (2015).

MEPS participants reported all medical diagnoses for each reference period at all five data collection points. An SMI diagnosis was reported by participants in the event of at least one of the following (AHRQ, 2014, 2015, 2016, 2017): 1) the respondent identified the condition as being associated with a hospital stay, outpatient medical visit, emergency room visit, home health episode, prescription medication purchase, or other medical provider visit; 2) the condition was identified as the reason for one of more episodes of disability days; 3) the condition was reported as ‘bothering’ the respondent during the reference period. These reported medical diagnoses were then assigned the matching ICD-9 condition code by professional coders and documented in the medical conditions file. To preserve confidentiality of MEPS participants, diagnosis codes were collapsed from the fully specified codes, which typically include up to two additional digits following a decimal point, to a more general three-digit code that captures a category of diagnoses (AHRQ, 2014, 2015, 2016, 2017). For example, the ICD-9 category code of 296 used in this study indicates a severe affective disorder such as bipolar disorder or major depressive disorder. The associated fully-specified ICD-9 codes collapsed into this category ranged from 296.00 to 296.99.

To properly identify participants with an SMI diagnosis, several variables were computed that counted the number of applicable diagnoses an individual had (i.e., 295, 296, 298), and categorized participants into mutually exclusive categories indicating the presence of any SMI diagnosis. Participants 18-70 years of age who reported an SMI diagnosis at any time during the survey were included in the sample for this study, providing a study sample of 648 individuals.

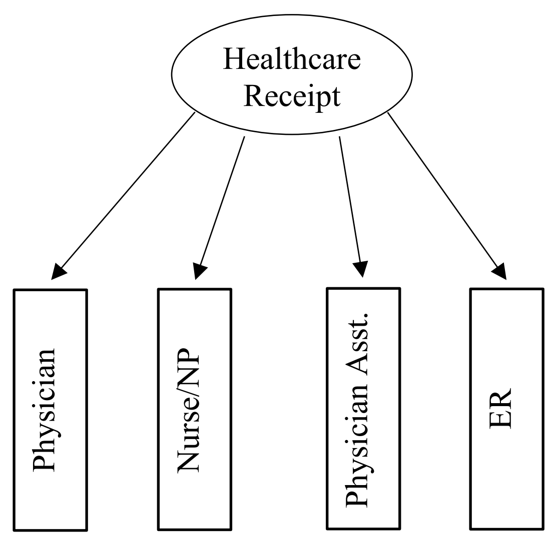
Variables

Priority health conditions. Presence of an AHRQ priority health condition in the first year of data collection (i.e., 2012 for panel 17, 2013 for panel 18, and 2014 for panel 19) was the exogenous variable, the "first link in a causal chain" (Vogt & Johnson, 2016, p. 149), for this study. AHRQ priority conditions were designated as such due to their high prevalence, expense, or policy relevance, and included: angina, heart attack, hypertension, high cholesterol, cancer, emphysema, chronic bronchitis, asthma, coronary heart disease, joint pain, other heart disease, stroke, diabetes, and arthritis (e.g., AHRQ, 2014, 2015). The MEPS included a dichotomous variable that indicated whether each respondent had each AHRQ priority health condition. Each separate diagnosis was included in descriptive analyses of the sample. Additionally, two variables were computed from these condition variables that reflect: 1) number of AHRQ priority health conditions, and 2) a dichotomous variable that specifies whether a person had any (i.e., one or more) AHRQ priority health condition.

Healthcare receipt. Healthcare receipt in year one of data collection (i.e., 2012 for panel 17, 2013 for panel 18, and 2014 for panel 19) was one of the endogenous variables in the model, those "caused by other variables in a causal system" (Vogt & Johnson, 2016, p. 141). Healthcare receipt was measured using four separate continuous variables regarding number of office-based physician visits, office-based nurse/nurse practitioner visits, office-based physician assistant visits, and emergency room visits. Survey respondents self-reported the number of visits they had in each category, for each year. An outlier of 362 was removed from the nurse/nurse practitioner indicator, and this value was replaced with a 46 (the next highest value). Univariate normality testing indicated severe violations to skewness and kurtosis for each of the four healthcare receipt indicators. Kendall & Stuart (1958) suggested an acceptable skewness range of -2.0 to 2.0, and an acceptable kurtosis range of -5.0 to 5.0. Given that each healthcare receipt indicator was outside this range, logarithmic transformations were performed. After the log-transformations were performed, violations to normality were still noted for all healthcare receipt indicators, except physician visits, due to the large number of 'zero' responses.

CFA. A single latent variable, that was proposed to represent healthcare receipt, was tested using confirmatory factor analysis (CFA). A one-factor model with the four indicators (see figure 2; physician office visits, nurse/nurse practitioner office visits, physician assistant office visits, and emergency room visits) was fit to the data.

Figure 2. Healthcare receipt measurement model



Weighted least squares means and variances adjusted (WLSMV) is the preferred estimator for analyzing non-normal data and categorical indicators with fewer than five categories (Beauducel

& Herzberg, 2006; Rhemtulla, Brosseau-Liard, & Savalei, 2012). Thus, WLSMV was used as the estimator for the CFA. Given that this proposed latent variable was exploratory, three CFA models were fit to the data that treated these indicators as continuous and categorical: 1) all four indicators included as continuous variables (please note, maximum likelihood was used as the estimator for this model because WLSMV cannot be used when all indicators are continuous); 2) physician office visit measure included as continuous, all others included as three-level categorical variables; and 3) physician office visit measure included as continuous, all others included as two-level categorical variables. Physician office visit was left as continuous in all CFA models because normality was indicated following log transformation for this variable.

Both general (e.g., chi-square, CFI/TLI, RMSEA) and specific (e.g., examination of residuals) fit indices were examined to determine the adequacy of fit for these measurement models, and parameters were examined in terms of statistical significance. All tested models were over-identified, which allowed for the specified model to be compared to a baseline model. The chi-square test of model fit compares the specified model to a baseline model that has no relationships between indicators or factors (Kline, 2016). A chi-square value that is not statistically significant ($p > .05$) indicates good fit between the specified model and the data, however the chi-square statistic can be strongly biased against larger sample sizes (Kline, 2016). Thus, it is recommended that alternative general fit indices also be examined.

In addition to chi-square, Mplus provides RMSEA, CFI, and TLI fit indices when the WLSMV estimator is used. RMSEA is a badness of fit test, meaning that a lower value indicates better fit, and unlike chi-square the specified model is not compared to a baseline model (Kline, 2016). Research suggests an RMSEA <. 05 (Browne & Cudeck, 1993), or RMSEA<.06 (Hu & Bentler, 1999), may indicate good model fit. Conversely, CFI and TLI are goodness of fit tests, meaning a higher value reflects better model fit, and a comparison is made to a baseline model (Kline, 2016). Additionally, CFI and TLI are less affected by sample size compared to chi-square (Schermelleh-Engel, Moosbrugger, & Müller, 2003). A CFI or TLI >.95 is considered to reflect good model fit (Hu & Bentler, 1999), and allows a researcher to reject the null hypothesis of bad fit.

Model 1, with all indicators included as continuous variables, did not converge at 1,000 iterations. While models 2 and 3 indicated good general fit with the data (see table 1), none of the parameters were statistically significant (see table 2).

Table 1. General model fit indicators for healthcare receipt CFA (n=648)

Model	Chi-Square X^2, df, p	RMSEA	CFI	TLI
All indicators continuous	Did not converge	--------	--------	--------
Physician visits continuous, all others categorical	.081, 2, p=.96	.000	1.000	1.026
Physician visits continuous, all others dichotomous	.689, 2, p=.71	.000	1.000	1.013

Table 2. Parameter estimates for healthcare receipt CFA (n=648)

Model	Standardized Coefficient	Standard Error	R^2	P-Value
Model 1	Did not converge	--------	--------	--------
Physician Office Visits				
Nurse/Nurse Practitioner Visits				
Physician Assistant Visits				
Emergency Room Visits				
Model 2				
Physician Office Visits	.496	.537	.246	.356
Nurse/Nurse Practitioner Visits	.025	.112	.001	.825
Physician Assistant Visits	.131	.139	.017	.346
Emergency Room Visits	.359	.391	.129	.359
Model 3				
Physician Office Visits	.495	.416	.245	.234
Nurse/Nurse Practitioner Visits	.031	.119	.001	.796
Physician Assistant Visits	.152	.119	.023	.204
Emergency Room Visits	.424	.359	.180	.237

Given these results, and that the specification of a latent construct was exploratory, the decision was made to include healthcare receipt as a manifest variable, with all sources of healthcare receipt summed together. Prior research on healthcare receipt/utilization for adults with SMI has examine each type of healthcare separately (Dickerson et al., 2003; Egede, 2007; Shen et al., 2008; Sullivan et al., 2006). While each type of healthcare was included separately in bivariate analyses to provide comparisons to prior research, and examine differences between types of receipt, summing all types of healthcare that a participant might have received together was necessary to simplify the SEM models, and provide a more complete picture of healthcare receipt. The summed variable had unacceptable levels of skewness and kurtosis, however values were within acceptable ranges following a log-transformation. Thus, the log-transformed version of the variable was used in all analyses, including the SEM path models.

HRQOL. HRQOL, another endogenous variable in the model, is a multidimensional measure of health, the preferred health status variable in economic analyses (Currie & Madrian, 1999), and is commonly used in social and behavioral science research. While diagnosis of a medical condition provides an objective indicator for one aspect of individual health, a medical diagnosis does not provide information about a person's physical and emotional functioning, which provides a more comprehensive representation of an individual's health. HRQOL was measured with the Medical Outcomes Survey Short-Form 12 (SF-12; Ware et al., 1996), a widely-used instrument for assessing HRQOL (Morris et al., 2012). MEPS participants completed the SF-12 in both the first and second year of data collection as part of the Adult Supplemental Questionnaire. SF-12 data collected during the first year of data collection were used for descriptive analyses. For hypothesis testing, SF-12 data collected during round four (i.e., second year) of data collection were used.

The SF-12 includes twelve questions that ask about a respondent's general health, physical and emotional limitations, and physical and emotional health characteristics (see table 3). Ten of the questions provide respondents with five valid response options; the remaining two questions (regarding physical limitations) provide respondents with three valid response options. Questions are additionally bounded by time: depending on the specific question, respondents are asked about their current health status, or symptoms within the last four weeks. Additionally, reverse scoring was completed for four of the items on the SF-12 (GH, BP, MH1, and VT, as noted in table 3) so that a higher value indicates a better health state (Ware, Kosinski, & Keller, 1998).

Table 3. SF-12 questions and response options

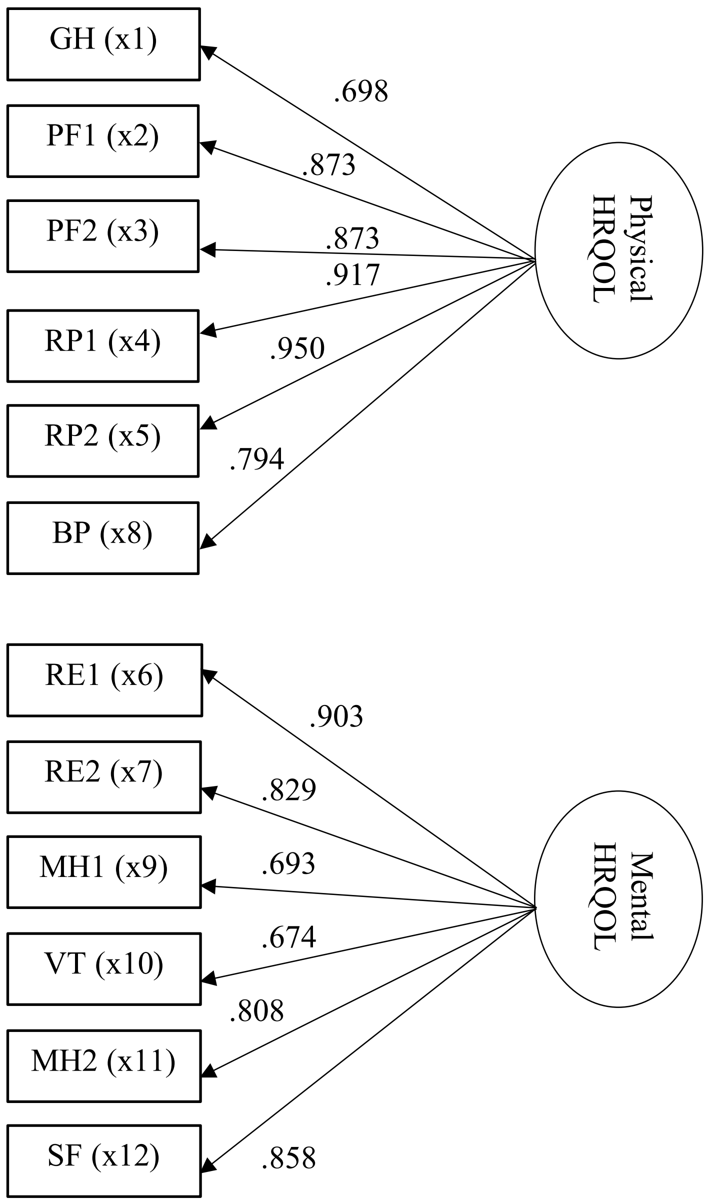
Physical HRQOL					
GH-In general, would you say your health is:	Excellent	Very Good	Good	Fair	Poor
PF1-Does your health now limit you in moderate activities, such as moving a table, pushing a vacuum cleaning, bowling, or playing golf:	Yes, limited a lot		Yes, limited a little		No, not limited at all
PF2-Does your health now limit you in climbing several flights of stairs:	Yes, limited a lot		Yes, limited a little		No, not limited at all
During the past 4 weeks:					
RP1-How much of the time have you accomplished less than you would like as a result of your physical health:	All of the time	Most of the time	Some of the time	A little of the time	None of the time
RP2-How much of the time were you limited in the kind of work or other activities as a result of your physical health:	All of the time	Most of the time	Some of the time	A little of the time	None of the time
BP-How much did pain interfere with your normal work (including both work outside the home and housework):	Not at all	A little bit	Moderately	Quite a bit	Extremely

<u>Mental HRQOL</u> **During the past 4 weeks:**					
RE1-How much of the time have you accomplished less than you would like as a result of your emotional health:	All of the time	Most of the time	Some of the time	A little of the time	None of the time
RE2-How much of the time did you do work or other activities less carefully than usual as a result of your emotional health:	All of the time	Most of the time	Some of the time	A little of the time	None of the time
MH1-How much of the time have you felt calm and peaceful:	All of the time	Most of the time	Some of the time	A little of the time	None of the time
VT-How much of the time did you have a lot of energy:	All of the time	Most of the time	Some of the time	A little of the time	None of the time
MH2-How much of the time have you felt downhearted and depressed:	All of the time	Most of the time	Some of the time	A little of the time	None of the time
SF-How much of the time has your physical health or emotional problems interfered with your social activities (like visit friends, relative, etc.):	All of the time	Most of the time	Some of the time	A little of the time	None of the time

The SF-12, its longer version the SF-36, and the even shorter version the SF-6, have been validated with several heterogeneous and homogeneous samples of individuals (Ware et al., 1996), including individuals with SMI (Chum et al., 2016; Salyers et al., 2000). HRQOL was represented as two latent variables in the analysis model. Measurement research has varied for the SF-12. Some research supports a non-recursive, uncorrelated, two-factor structure for the SF-12 as a measure for HRQOL, one representing an individual's physical HRQOL and the second representing an individual's mental HRQOL (e.g., Gandek et al., 1998; Ware et al., 1998). Other research found that a correlated two-factor model had better fit with the data (Anagnostopoulos, Niakas, & Tountas, 2009; Hann & Reeves, 2008). Additionally, forcing a correlation between factors makes conceptual sense given the strong relationship between body and mind. Research has also supported correlated indicator error terms for items on the same subscale, and with similar wording (Maurischat, Ehlebracht-König, Kühn, & Bullinger, 2006; Wilson, Tucker, & Chittleborough, 2002), as well as allowing the general health indicator to load on both latent factors (i.e., crossload). Using data from a sample of individuals with SMI, Chum and colleagues (2016) tested four measurement models that progressively added parameters to reflect the research described above. The authors found that a correlated two factor model, with correlated error terms, and the general health indicator cross-loading on both latent factors, had the best fit to the data (Chum et al., 2016). Due to the varying measurement research, confirmatory factor analysis was performed to examine the factor structure of the SF-12 using the WLSMV estimator.

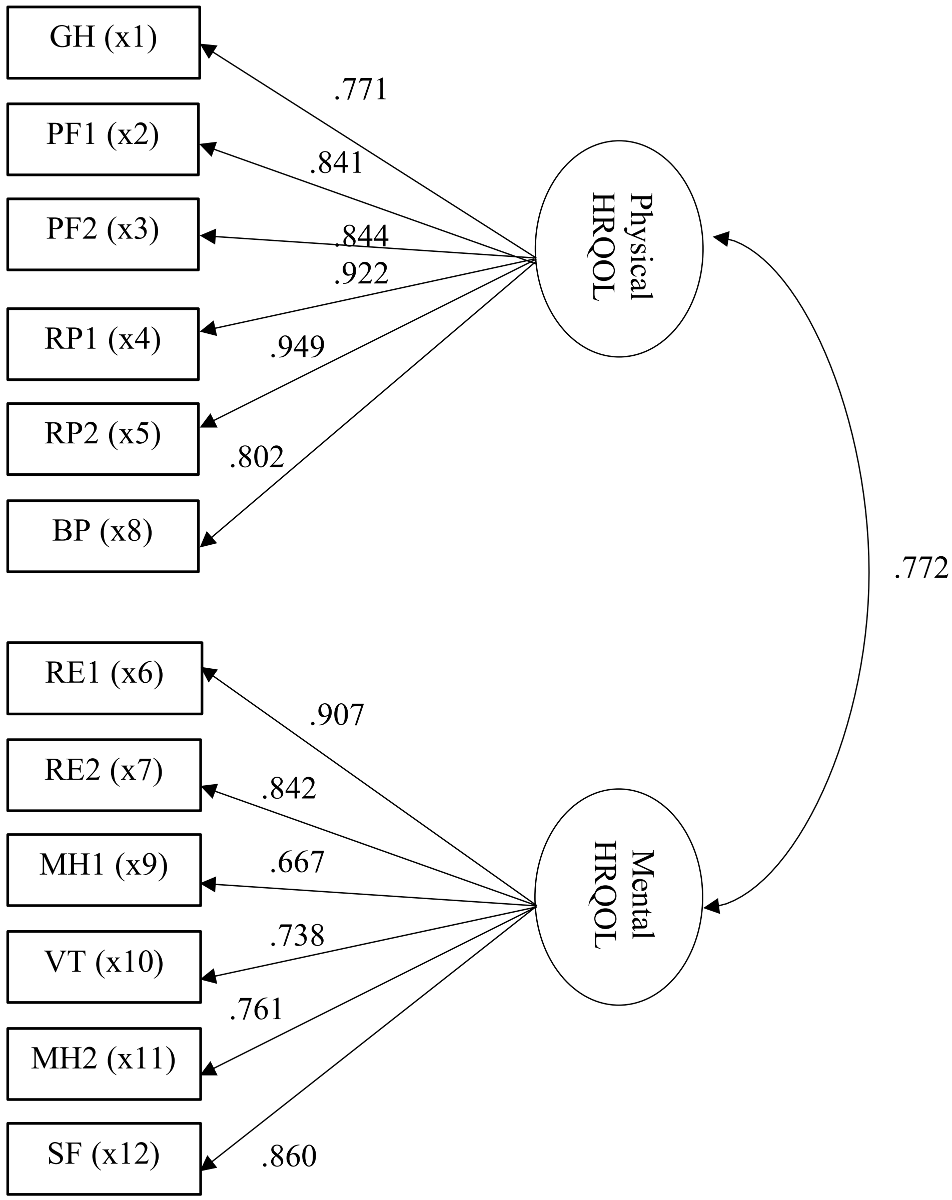
CFA. Four measurement models (see figures 3-6) were fit to the data and were evaluated for model fit and significance of parameters. All models were over-identified, and included two latent factors representing physical HRQOL and mental HRQOL. Congruent with Chum et al. (2016), the following models were tested: 1) two uncorrelated factors (see figure 3); 2) two correlated factors (see figure 4); 3) two correlated factors with correlated error residuals among selected indicators (see figure 5); and 4) two correlated factors with correlated error residuals as specified in model three, and the first indicator cross-loading on both factors (see figure 6). The standardized parameters estimated by each CFA model are reflected in each figure.

Figure 3. SF-12 CFA, two uncorrelated latent factors



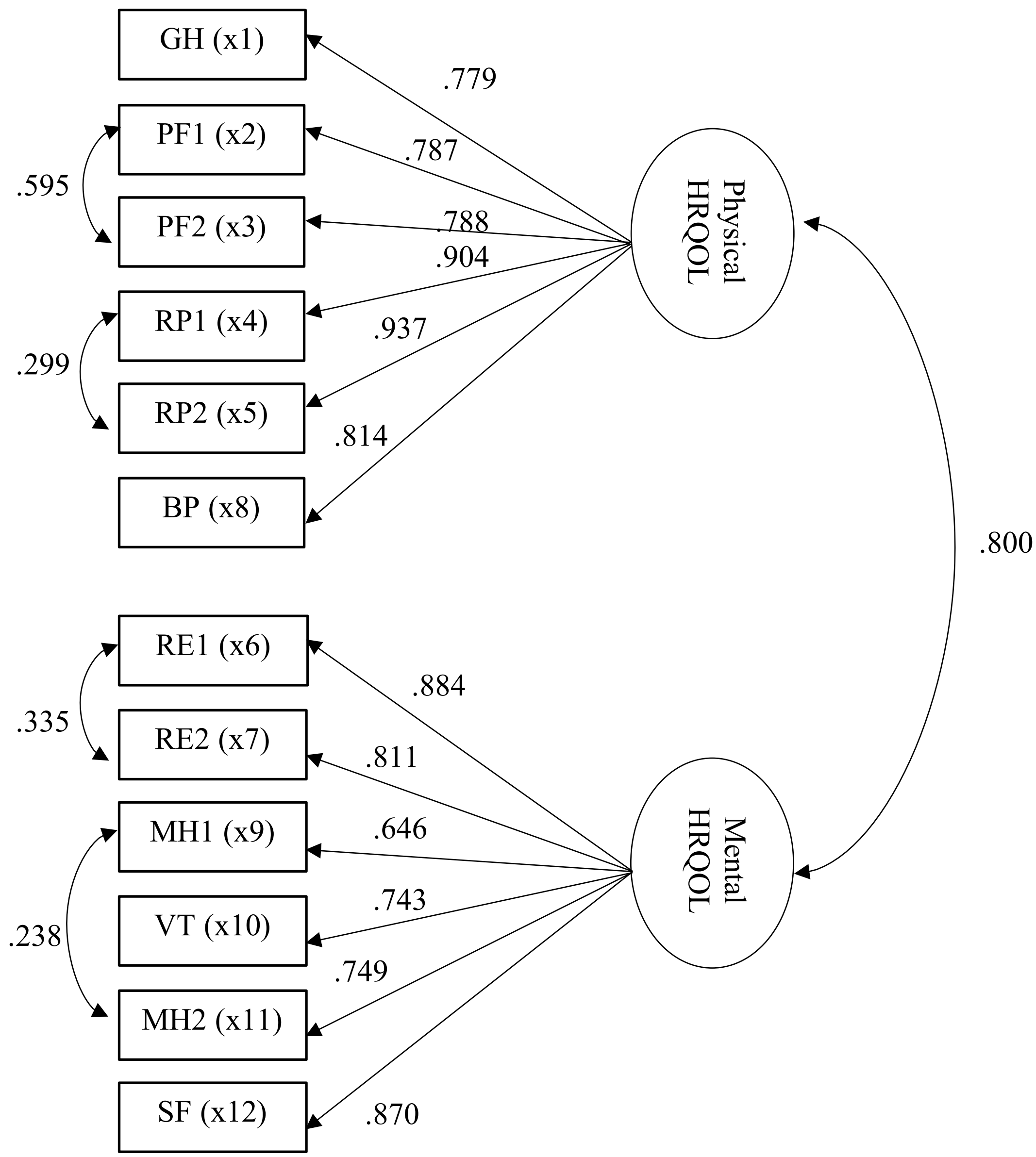
Notes: Standardized parameter statistics are provided. GH-General Health; PF1-Physical Functioning, moderate activities; PF2-Physical Functioning, climbing several flights of stairs; RP1-Role Functioning (physical), accomplished less; RP2-Role Functioning (physical), limited in the kind of work or other activities; BP8-Bodily Pain; RE1-Role Functioning (emotional), accomplished less; RE2-Role Functioning (emotional), less carefully than usual; MH1-Mental Health, calm and peaceful; VT-Vitality, energy; MH2-Mental Health, downhearted and depressed; SF-Social Functioning.

Figure 4. SF-12 CFA, two correlated latent factors



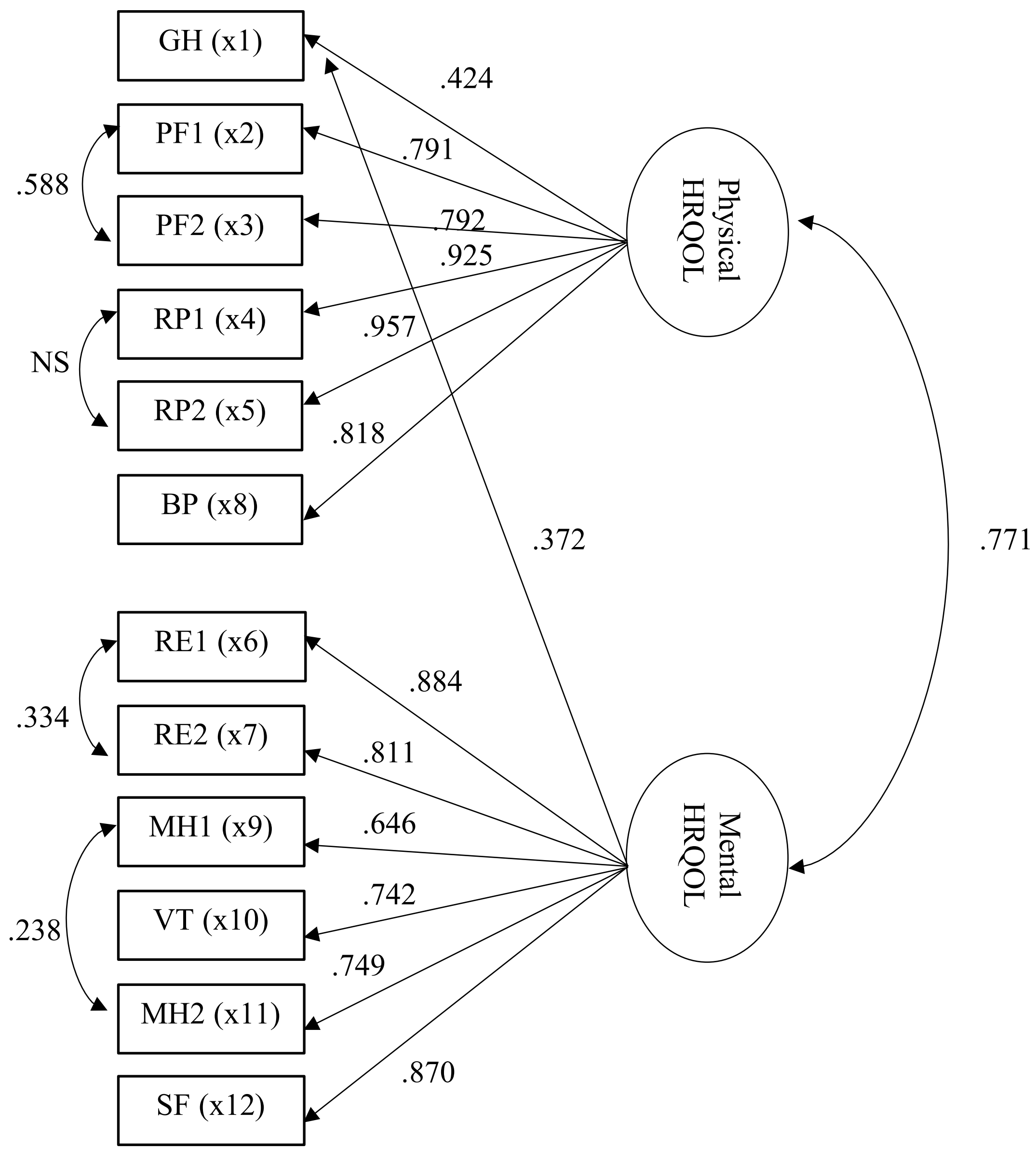
Notes: Standardized parameter statistics are provided. GH-General Health; PF1-Physical Functioning, moderate activities; PF2-Physical Functioning, climbing several flights of stairs; RP1-Role Functioning (physical), accomplished less; RP2-Role Functioning (physical), limited in the kind of work or other activities; BP8-Bodily Pain; RE1-Role Functioning (emotional), accomplished less; RE2-Role Functioning (emotional), less carefully than usual; MH1-Mental Health, calm and peaceful; VT-Vitality, energy; MH2-Mental Health, downhearted and depressed; SF-Social Functioning.

Figure 5. SF-12 CFA, two correlated latent factors with correlated errors



Notes: Standardized parameter statistics are provided. GH-General Health; PF1-Physical Functioning, moderate activities; PF2-Physical Functioning, climbing several flights of stairs; RP1-Role Functioning (physical), accomplished less; RP2-Role Functioning (physical), limited in the kind of work or other activities; BP8-Bodily Pain; RE1-Role Functioning (emotional), accomplished less; RE2-Role Functioning (emotional), less carefully than usual; MH1-Mental Health, calm and peaceful; VT-Vitality, energy; MH2-Mental Health, downhearted and depressed; SF-Social Functioning.

Figure 6. SF-12 CFA, two correlated latent factors with correlated errors and cross-loading



Notes: Standardized parameter statistics are provided. NS-Not statistically significant. GH-General Health; PF1-Physical Functioning, moderate activities; PF2-Physical Functioning, climbing several flights of stairs; RP1-Role Functioning (physical), accomplished less; RP2-Role Functioning (physical), limited in the kind of work or other activities; BP8-Bodily Pain; RE1-Role Functioning (emotional), accomplished less; RE2-Role Functioning (emotional), less carefully than usual; MH1-Mental Health, calm and peaceful; VT-Vitality, energy; MH2-Mental Health, downhearted and depressed; SF-Social Functioning.

As was the case with the healthcare receipt CFA, general and specific fit indices were examined (i.e., X^2, RMSEA, CFI, TLI, and indicator residuals). Additionally, given that multiple models were tested that were nested within each other, chi-square difference testing was completed. When the WLSMV estimator is used, the typical method for computing differences in chi-square is not appropriate. Instead, the DIFFTEST command is used which compares the model with lower degrees of freedom (i.e., less restricted) to the model with higher degrees of freedom (i.e., more restricted; Muthén & Muthén, 2017). A statistically significant result ($p<.05$) from this test indicates that the less restrictive model provides better fit than the more restrictive model, and should be retained (Kline, 2016; Muthén & Muthén, 2017).

General and specific fit indices are included in table 4. Model fit indices provided conflicting results regarding model fit. The chi-square test for model fit indicated poor model fit, however this is not surprising given that the chi-square test penalizes larger sample sizes (Kline, 2016). It is generally recommended that CFI, TLI, and RMSEA be used to assess model fit for single model analyses, and that chi-square difference tests be used multiple nested models are tested (Schreiber, Nora, Stage, Barlow, & King, 2006). The RMSEA test statistic also indicated poor model fit for all four models, but the CFI and TLI statistics indicated good model fit for models 2-4.

Table 4. General and specific model fit indicators for SF-12 CFA (n=590)

Model	**Chi-Square X^2, df, p**	**X^2 Diff. Test**	**RMSEA**	**CFI**	**TLI**	**# Absolute Residuals >.1**
Model 1	5564.101, 54, p<.001	--------	.416	.668	.619	37
Model 2	709.360, 53, p<.001	845.239, 1, p<.001	.145	.963	.954	10
Model 3	548.064, 49, p<.001	139.312, 4, p<.001	.131	.972	.962	5
Model 4	498.728, 48, p<.001	33.359, 1, p<.001	.126	.974	.965	3

Note: Chi-square difference test completed using the DIFFTEST function in Mplus. Statistic provided includes the difference in chi-square value and degrees of freedom between the two nested models, and the p-value of this difference.

In addition to assessing general fit, indicator residuals can be examined to assess specific fit. Absolute residuals > .1 are concerning, and models with fewer residuals >.1 are considered to be more representative of the data (Kline, 2016). In terms of specific fit, the number of concerning residuals decreased as additional parameters were specified, and the final model (model 4) only indicated three residuals >.1 (x3-x9=.101, x3-x11= -.147, x4-x11= -.199). Given that nested models were tested, the X^2 difference test was used to compare models to provide information on which model provides the best fit with the data (see table 4). Results indicated that each re-specification of the model significantly improved model fit, suggesting that model 4 had the best fit with the data. This finding is congruent with SF-12 measurement research that included a sample of adults with SMI by Chum et al. (2016).

After assessing the model fit statistics, model 4 with two correlated latent factors, correlated indicator errors, and a cross-loading on x1 (see figure 6) was chosen for inclusion in the full SEM model. Assessing model fit when fit indices provide conflicting results can be difficult, however if the majority of fit indices suggest good fit, then there is probably good fit with the data (Schreiber et al., 2006). While RMSEA indicated concerns with model fit, CFI, TLI, the small number of absolute residuals > .1, and the chi-square difference test suggested model 4 provided the best fit with the data. Indicators that loaded on only one factor had high standardized factor loadings (Cohen, 1969), ranging from .646 to .957. The general health indicator (x1) loads on both factors and produces partial factor loadings: The factor loadings reflect its loading while holding its relationship with the other factor constant. Thus, the size of the factor loadings cannot be compared to the other loadings.

Employment. Employment, the final endogenous variable in the model, was measured using a categorical employment status variable. Participants who reported that they were employed at the time of the interview date, or reported they had a job to return to at the interview date, were categorized as employed. Those who reported they were not employed at the time of the interview date, even if they were employed at another time during the round reference period, were categorized as unemployed. For descriptive analyses, baseline employment status data were used; for hypothesis testing, employment status (i.e., employed vs. unemployed) data from the final round of data collection were used. In addition, two employment-related variables were used to describe the employment characteristics for persons with SMI, including a continuous and categorical variable regarding disability days for the entire survey period, and a variable that reported why an individual was unemployed at baseline.

Covariates. Several variables were included as covariates due to their relationships with health, healthcare, and employment (Andersen, 1995; Andersen & Newman, 1973; Birch et al., 2000; Chirikos & Nestel, 1985; Grossman, 1972; Solar & Irwin, 2010). Baseline data from the first round of data collection were used for all covariates.

Sex. A respondent's sex was collected on the MEPS using a single self-report item with two possible response options: male or female. Research indicates that sex is related to the presence of some chronic physical health conditions, HRQOL, and employment. For example, women suffer from higher morbidity for many health conditions (Read & Gorman, 2010), are more likely to have co-occurring SMI and diabetes (e.g., Banerjea, Sambamoorthi, Smelson, & Pogach, 2007; Razzano et al., 2015), and have a lower mean physical and mental HRQOL scores compared to men (Fleishman & Lawrence, 2003). Available research also suggests that the relationship between health and employment differs for males and females (e.g., Chirikos & Nestel, 1985; Ettner et al., 1997; Kahn, 1998; Luo et al., 2010).

Race/ethnicity. Race and ethnicity was measured with a categorical variable with five mutually-exclusive response options: Hispanic, White only, Black only, Asian only, and other race or multi-race. Due to the small number of participants who reported racial identities other than White, Black, or Hispanic, the SEM model only included categories of White and non-White. While this does not permit the examination of differences among non-White racial and ethnic identities, these categories reflect differences in privilege due to socially constructed racial and ethnic stratifications. Race and ethnicity, as indicators of social structure, are related to healthcare utilization (Andersen, 1995), and racial and ethnic disparities in health are well-documented. Research suggests minoritized persons of color have poorer health on many specific health diagnosis measures (e.g., obesity, diabetes, asthma) compared to White individuals (e.g., Braveman, 2012; The Office of Minority Health, 2015; Williams & Mohammed, 2013), and disparities are similarly found in investigations of co-occurring mental and physical health conditions (e.g., Cabassa et al., 2013; McEvoy et al., 2005; Nasrallah et al., 2006; Razzano et al., 2015). While disparate rates of diagnoses are prevalent, there do not seem to be strong racial and ethnic differences in HRQOL scores (Fleishman & Lawrence, 2003). Employment status differs by race and ethnicity (Bureau of Labor Statistics, 2017a, 2017b), and the relationship between health and employment may also differ by race (e.g., Chirikos & Nestel, 1985).

Age. Age was measured continuously and reflects a respondent's age at the beginning of MEPS participation. It is well-known that an individual's health tends to worsen with age, and older individuals tend to have more chronic physical health conditions (e.g., Fortin, Bravo, Hudon, Vanasse, & Lapointe, 2005). Age is also related to HRQOL, but the specific relationship depends on the component: physical HRQOL tends to decrease with age, but mental HRQOL increases (Fleishman & Lawrence, 2003). Furthermore, age is related to employment status (Bureau of Labor Statistics, 2017c). Relationships between employment status and age include consideration of retirement. Full retirement age, as defined by the Social Security Administration (n.d.), was considered 65 years of age for individuals born prior to 1938, however full retirement age has gradually increased to its current definition of 67 years for individuals born after 1959.

Education. Education was used as a covariate to represent an individual's SES. Education was measured as a six-level categorical (i.e., ordinal) variable, which was treated as continuous in the primary model. Education is a strong predictor of an individual's health (e.g., Grossman, 1972, 2000; Telfair & Shelton, 2012) and healthcare utilization (e.g., Gaskin & Roberts, 2012). Education is also related to an individual's employment status (Bureau of Labor Statistics, 2017d) and is related to relationships between health and employment (e.g., Kahn, 1998). Similarly, individuals with no high school degree, or a high school degree only, have significantly lower physical and mental HRQOL scores, compared to those with higher levels of education (Fleishman & Lawrence, 2003).

Health insurance status. MEPS includes several variables related to an individual's health insurance status. Specific health insurance types (i.e., any public, any private, uninsured) were used to describe the sample, but a dichotomous variable that indicated whether an individual has any source of health insurance was included in multivariate analyses. Health insurance status was included due to its strong relationship with healthcare utilization (e.g., Andersen, 1995; Andersen & Newman, 1973; Gaskin & Roberts, 2012) and health (e.g., Gilmer et al., 2016; Sommers et al., 2016).

Disability income status. Disability income status was measured with several categorical variables that indicated whether an individual receives SSI only, SSDI only, SSI and SSDI, or no disability income. These variables were computed using individual variables that reported the amount of SSI or SSDI income received, where an income of $0 indicated no disability income receipt and an income of $1 of more indicated disability income receipt. In the multivariate models, a dichotomous variable that indicated whether an individual had no disability income or any disability income was included because a disability determination suggests that a person is unable to work due to their illness/disability. Thus, disability income receipt is strongly connected to employment status and health.

Analysis Plan

A set of descriptive analyses were completed using SPSS to describe the demographics of the sample, characteristics of employment, healthcare receipt, and HRQOL, for individuals with SMI and co-occurring physical health conditions. Bivariate analyses (chi-square, t-test, or ANOVA, as appropriate) were completed to examine group differences in healthcare receipt, HRQOL, and employment, between those with and without co-occurring physical health conditions. Then, structural equation modeling (SEM) was completed in Mplus Version 7 to examine pathways between co-occurring physical health conditions, healthcare receipt, HRQOL, and employment, for individuals with SMI. SEM was chosen for its ability to test theoretical models, include latent variables, and represent measurement error (Kline, 2016).

Maximum Likelihood (ML) is the default estimator used for CFA and SEM in Mplus. However, ML can provide biased estimates and standard errors when applied to non-normal ordinal and interval-level variables with skewness and kurtosis values greater than the absolute value of 2.0 (Muthén & Kaplan, 1985). Thus, WLSMV was used as the estimator for SEM path analysis due to it being the preferred estimator for analyzing non-normal data and categorical indicators with fewer than five categories (Beauducel & Herzberg, 2006; Rhemtulla et al., 2012). The default method of pairwise deletion was used in the case of missing data. The variables with the most missing data were those derived from the SF-12 measure. The SF-12 was administered using a supplemental mailed survey, and some data were lost due to non-return. However, only 9% of the sample was missing data for this measure (n=590 vs. N=648). Missingness was not allowed in terms of priority health condition and covariates, thus the full sample size for the analyses excluded participants missing data on any of these indicators (Muthén & Muthén, 2017). The final sample size for the SEM analysis was 645, a loss of only 3 participants.

Direct relationships. Mplus provides probit regression coefficients for relationships that include a binary outcome, when the WLSMV estimator is used. While the probit regression coefficients can provide information regarding strength and direction of a relationship, they cannot be meaningfully interpreted in the same way as other types of regression coefficients (e.g., linear, logistic), because the coefficients refer to a latent variable computed by Mplus to represent the binary outcome (Muthén & Asparouhov, 2015). To provide practical interpretations for the relationships with a binary outcome (i.e., employment) predicted probabilities were computed using the following equation:

$$\Phi[(-\tau + \gamma x)\, V(\delta)^{-1/2}]$$

Where: Φ represents the standard normal z-distribution, τ represents the threshold of the latent outcome variable (i.e., employment status), γ represents the probit regression coefficient for the relationship between the latent outcome variable and the predictor variable, and $V(\delta)$ represents the variance of the latent outcome (Muthén & Muthén, 2011, 2017). The resulting value is a z-score, which can then be used to provide an estimate of the probability of the observed event occurring, in this case employment. Predicted probabilities were computed for direct relationships between priority health conditions and employment, and physical or mental HRQOL and employment.

Mediation analyses: Partial mediation was hypothesized and tested using SEM. The Sobel test, completed by multiplying the direct effect path coefficients together, is often used to test statistical significance of indirect effects in mediation analyses. Regression paths with small coefficients will yield very small coefficients for indirect effects, making it more difficult to detect statistical significance. Further, the Sobel test incorrectly assumes a normal distribution for the indirect effect (MacKinnon, Fairchild, & Fritz, 2007), providing biased mediation results due to non-normality. Alternatively, bias-corrected (BC) bootstrapped confidence intervals can be used to examine indirect effects. This method provides accurate confidence intervals and improves statistical power for detecting indirect effects without increasing the risk for Type I errors (MacKinnon, Lockwood, & Williams, 2004), however survey weights cannot be included. Both SEM models were tested using the Sobel method with survey weights, and BC bootstrapped confidence intervals without survey weights, and compared for differences/similarities. For the weighted analyses, mediation was indicated if Wald-z tests for the indirect effects had a p-value less than .05. In the case of BC bootstrapped confidence intervals, which are computed by Mplus, mediation was indicated if the 95% confidence interval for the indirect effect did not contain zero (MacKinnon et al., 2004).

Chapter 4: Results

Descriptive Statistics

The final sample included 648 individuals with SMI, between the ages of 18 and 70 years old. Table 5 describes demographic characteristics for the sample.

Table 5. Demographic characteristics of sample (N = 648)

Variable name	Number (Percent)
Sex	
Male	261 (40.3%)
Female	387 (59.7%)
Education	
Eighth grade or less	29 (4.5%)
9th-12th grade, no diploma	103 (16.0%)
GED or HS diploma	203 (31.6%)
Some college	210 (32.7%)
Bachelor's degree	68 (10.6%)
Master's degree or higher	30 (4.7%)
Race/Ethnicity	
Caucasian/White	348 (53.7%)
African American/Black	149 (23.0%)
Asian	9 (1.4%)
Other or Multiple Races	29 (4.5%)
Hispanic	113 (17.4%)
Health Insurance	
Private Health Insurance	205 (31.6%)
Public Health Insurance	367 (56.6%)
No Insurance	76 (11.7%)
Disability Income Status	
Any disability income	284 (43.8%)
Received SSI	168 (25.9%)
Received SSDI	152 (23.5%)
Received both SSI and SSDI	36 (5.6%)

Continuous Variables

Variable Name	*Skewness*	*Kurtosis*	$\bar{x}$	Median	*SD*
Age	-.057	-1.014	42.82	43.00	13.34
Education[1]	.085	-.172	2.43	2	1.153

Note. Number of missing not included in the calculation of number, percent, or mean. Demographic data based on information collected in round 1 of data collection.
[1]Measured on a scale of 0-5. Mean and median fall within the "GED or HS Diploma" category.

The mean age of the sample was 42.82 years, and the sample was primarily female (59.7%), identified as Caucasian/white (68.1%), and had public health insurance (56.6%). A relatively equal number of participants reported having a GED/high school diploma (31.6%) or some college (32.7%), and 20.5% of participants had less than a high school education. While the majority of participants did not receive disability income (56.2%), roughly a quarter of participants reported receiving each SSI (25.9%) or SSDI (23.5%), and 5.6% of participants reported receiving both SSI and SSDI.

Table 6 provides descriptive statistics for health characteristics of the sample. The study sample had a mean BMI of 30.65, which is considered obese according to standards specified by the Centers for Disease Control and Prevention (2017), reported an average of 2.7 priority health conditions, had a mean SF-12 PCS of 43.93, and had a mean SF-12 MCS of 38.64. The mean PCS and MCS scores of the sample are lower than average scores found in the general U.S. population (Fleishman & Lawrence, 2003). Individuals with SMI (i.e., the study sample) had significantly higher mean BMI and number of physical health conditions, and significantly lower mean PCS and MCS, compared to those without SMI; significantly higher rates of all priority health conditions compared to those without SMI were also observed (findings not shown). Approximately 81% of individuals with SMI reported being diagnosed with at least one priority health condition. Among those with reported a priority health condition, most commonly individuals reported one (16.5%), two (15.6%), or three (17.3%) priority health conditions. A total of approximately 29% of individuals, however, reported between four and seven priority health conditions.

Table 6. Health characteristics of sample (N = 648)

Categorical Variables	
Variable name	N(%)
Physical Health Condition	
Yes (At least one)	526 (81.3%)
Number of Physical Health Conditions	
0	121 (18.7)
1	107 (16.5%)
2	101 (15.6%)
3	112 (17.3%)
4	85 (13.1%)
5	52 (8.0%)
6	28 (4.3%)
7	22 (3.4%)
8	7 (1.1%)
9	3 (.5%)
10	4 (.6%)
11	3 (.5%)
12	2 (.3%)
Physical Health Diagnosis	
Angina	23(3.6%)
Arthritis	252(38.9%)
Asthma	159(24.6%)
Cancer	64(9.9%)
Chronic Bronchitis	47(7.3%)
Coronary Heart Disease	35(5.4%)
Diabetes	95(14.7%)
Emphysema	40(6.2%)
Heart Attack	32(4.9%)
High Cholesterol	269(41.6%)
Hypertension	285(44.0%)
Joint Pain	320(49.9%)
Other Heart Disease	84(13.0%)
Stroke	42(6.5%)

Continuous Variables					
Variable Name	*Skewness*	*Kurtosis*	$\bar{x}$	Median	*SD*
Body Mass Index	1.01	1.56	30.65	29.60	7.82
# Physician Visits[1]	.014	-.546	7.95	5.00	11.91
# Nurse/Practitioner Visits[1]	2.74	8.06	.78	0	3.18
# Physician Assist Visits[1]	5.01	27.98	.18	0	.997
# Emergency Room Visits[1]	2.74	8.06	.63	0	1.20
# All types of visits[1]	-.108	-.341	9.54	6.00	12.76
# Physical Health Conditions	.99	1.25	2.70	2.00	2.26
SF-12 PCS	-.35	-.77	43.93	45.49	12.34
SF-12 MCS	-.17	-.59	38.64	39.39	13.55

Note. Health data collected during the first year of data collection. Number of missing not included in the calculation of number, percent, or mean.
* p<.05, **p<.01, ***p<.001
[1]Skewness and kurtosis are provided for the log-transformed versions of these variables due to severe violations to normality. Mean, median, and standard deviation reflect non-transformed values.

The five most common diagnoses among the study sample were joint pain (49.9%), hypertension (44.0%), high cholesterol (41.6%), arthritis (38.9%), and asthma (24.6%). These five diagnoses were also the most common for those without SMI, however the incident rates were significantly higher for those with SMI (findings not shown). The disparity between those with and without SMI was the greatest for asthma: adults with SMI were approximately 2.5 times more likely to report a diagnosis of asthma (24.6% vs. 10.8%). Further, while statistically significant, only marginal differences were noted for angina (3.6% vs. 1.8%) and coronary heart disease (5.4% vs. 3.8%).

Table 7 contains descriptive information on employment characteristics for the sample. Approximately 30% of study participants reported being employed at the beginning of the survey period. Among those who were unemployed, the vast majority reported not working due to illness/disability (69.9%). Notably, while approximately 70% of participants reported not working due to illness/disability, only 43.8% of participants reported receiving disability income.

Table 7. Employment characteristics of sample (N = 648)

Categorical Variables	
Variable name	Number (Percent)
Employment Status	
Employed	191 (29.6%)
Unemployed	453 (70.3%)
Reason for Not Working	
Could not find work	31 (10.6%)
Retired	20 (6.8%)
Unable to work because of illness/disability	204 (69.9%)
Going to school	7 (2.4%)
Taking care of home or family	20 (6.8%)
Wanted some time off	1 (.3%)
Maternity/paternity leave	1 (.3%)
On temporary layoff	2 (.7%)
Other	6 (2.1%)
Number of missed workdays due to illness/injury[1]	
0 days	131 (40.4%)
1-5 days	82 (25.3%)
6-10 days	35 (10.8%)
11-15 days	17 (5.2%)
16-20 days	20 (6.2%)
21 days or more	39 (12.0%)

Continuous Variables					
Variable Name	*Skewness*	*Kurtosis*	$\bar{x}$	Median	*SD*
# Missed Workdays-Illness/Injury[1]	.623	-.810	9.28	2.00	18.62

Note. Employment data based on information collected during the first round of data collection. Number of missing not included in the calculation of number, percent, or mean.

[1]Reflects the number of missed workdays during the entire survey period (18-24 months, depending on timing of the individual's data collection), for those employed at any time during the survey period (n=324). Skewness and kurtosis are provided for the log-transformed version of this variable due to severe violations to normality. Mean, median, and standard deviation reflect non-transformed values.

Bivariate Differences in Healthcare Receipt

Research question one sought to examine differences in healthcare receipt for adults with co-occurring conditions, compared to adults to SMI only. Table 8 displays results of independent t-tests of each category of healthcare receipt (i.e., physician, nurse/nurse practitioner, physician assistant, and emergency room), and for all categories of healthcare receipt summed together, by the presence of at least one priority health condition. To minimize violations due to non-normality, the log transformed versions of these variables were used to complete t-tests. Results indicated that individuals with a priority condition received more healthcare visits from physicians (t = -5.805, p<.001), physician assistants (t = -2.806, p<.01), the emergency room (t = -4.488, p<.001), and from all sources of healthcare combined (t = -6.214, p<.001); no significant difference was found for nurse/nurse practitioner visits. Additionally, number of priority health conditions was significantly positively correlated with the total number of healthcare visits an individual reported (*r* = .331, p<.01).

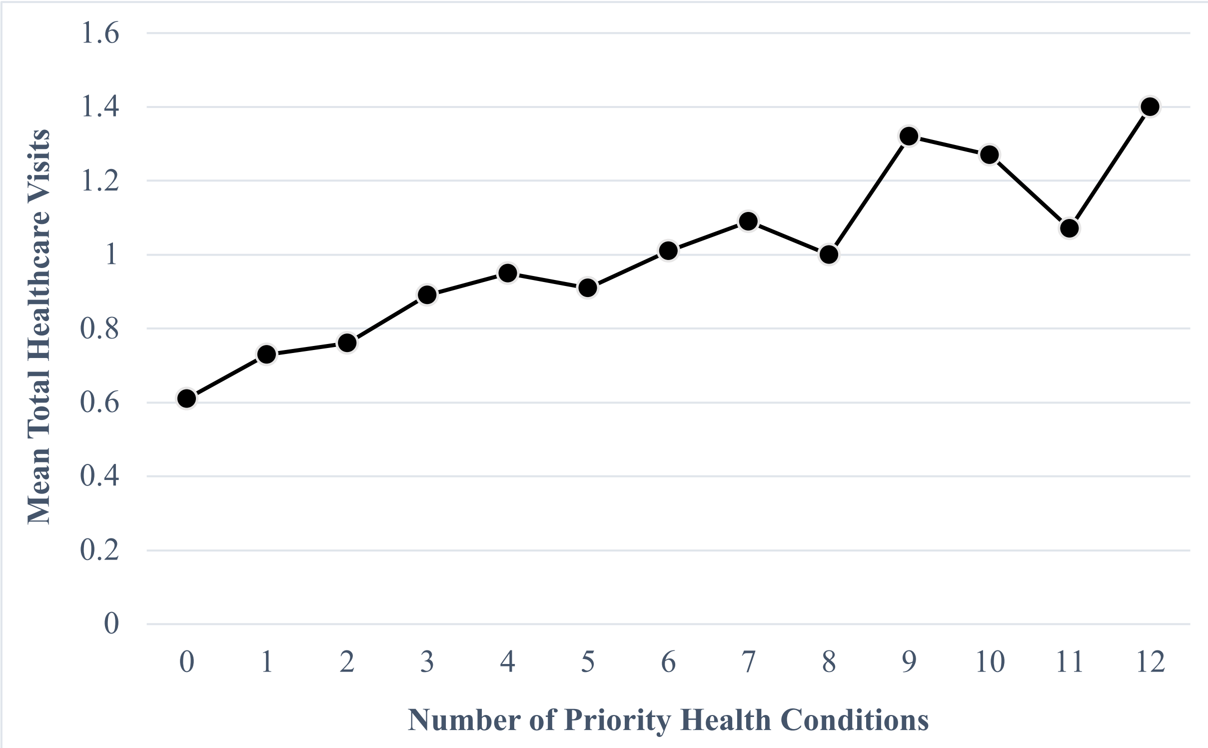
Table 8. Independent t-tests of healthcare receipt, by presence of priority condition (n=648)

Variable name	No Priority Condition $\bar{x}$	Priority Condition $\bar{x}$	t
Physician Visits	4.17	8.82	-5.805***
Nurse/NP Visits	.74	.79	-1.445
Phys. Assist. Visits	.06	.21	-2.806**
Emergency Room	.31	.70	-4.488***
Total all visits	5.27	10.52	-6.214***

Note. Priority condition and healthcare receipt data collected during first year of data collection. The log-transformed versions of the healthcare variables were used to complete t-tests due to severe violations to normality. Means reflect non-transformed values.
* p<.05, **p<.01, ***p<.001

Figure 7 graphically depicts the relationship between these variables, in terms of mean total healthcare visits by number of priority health conditions. The line trends downward until eight priority health conditions, at which point the line direction is less consistent. This may be due to the fact that very few people reported eight or more priority health conditions, thus the mean score is based on few individuals (see table 6) and may be less reliable. These results provide support for hypothesis 1 for all types of healthcare receipt, except nurse/nurse practitioner visits.

Figure 7. Graph of number of priority health conditions by mean log-transformed total healthcare visits



Bivariate Differences in HRQOL

Research question two sought to examine differences in physical and mental HRQOL for adults with SMI and priority heath conditions, compared to adults with SMI only. Table 9 displays results of the independent t-tests of physical HRQOL and mental HRQOL, as measured by observed scores of the SF-12 PCS and MCS, by the presence of at least one priority health condition. Results indicated that participants with at least one priority health condition had lower scores for both physical HRQOL ($t = 10.524$, $p<.001$) and mental HRQOL ($t = 3.466$, $p<.01$). There were also statistically significant correlations between the number of priority health conditions that a participant had, and their physical HRQOL ($r = -.539$, $p<.001$) and mental HRQOL (Pearson $r = -.138$, $p = .001$).

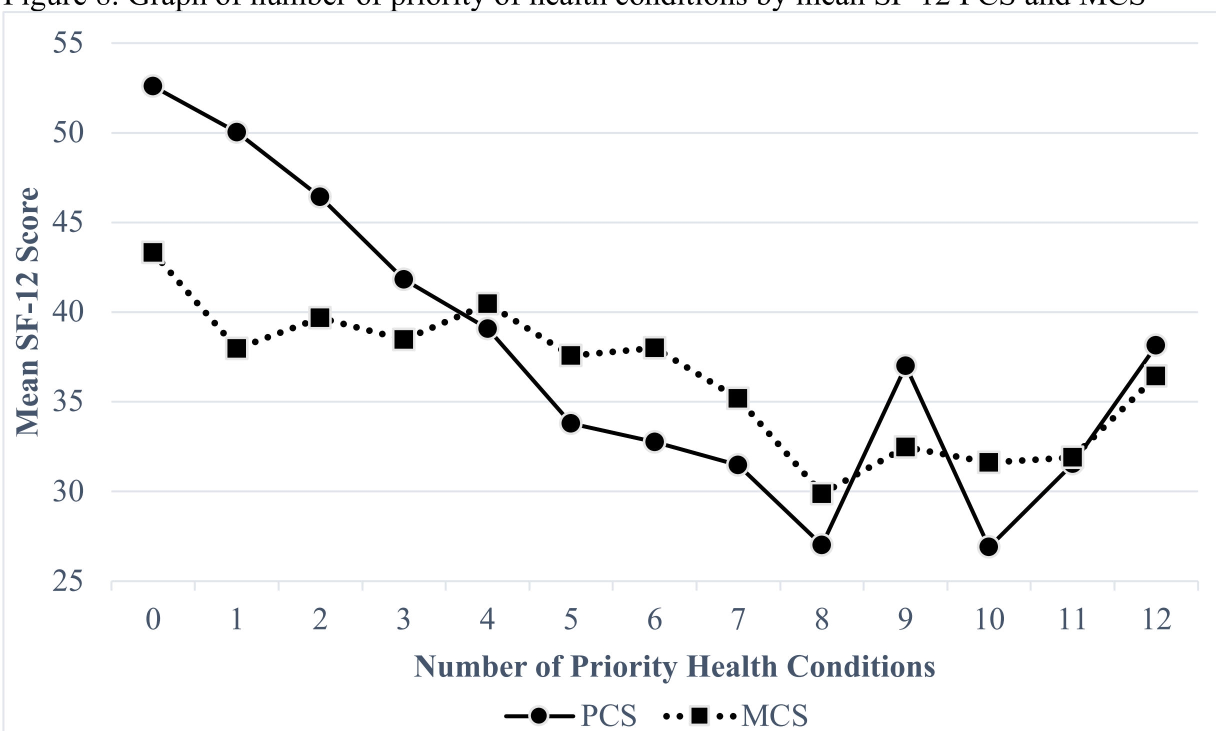
Table 9. Independent t-test of SF-12 PCS and MCS, by presence of a priority condition (n=588)

Variable name	No Priority Condition $\bar{x}$	Priority Condition $\bar{x}$	t
SF-12 PCS	52.59	41.62	10.524***
SF-12 MCS	43.31	38.40	3.466**

Note. Priority condition data collected during first year of data collection. SF-12 data collected during the second year of data collection.
* p<.05, **p<.01, ***p<.001

Figure 8 graphically depicts the relationships between number of priority health conditions and mean PCS and MCS scores for all participants with the respective number of conditions. For both PCS and MCS, the line again trends downward until eight priority health conditions, but then becomes less consistent, likely due to the fact that very few people reported eight or more priority health conditions. These results provide support for hypotheses 2.1 and 2.2, indicating that co-occurring physical health conditions are related to lower physical HRQOL and lower mental HRQOL.

Figure 8. Graph of number of priority of health conditions by mean SF-12 PCS and MCS



Bivariate Differences in Employment

Research question three examined differences in employment status and lost workdays due to illness for adults for co-occurring conditions, compared to adults to SMI only. Table 10 displays crosstab and Pearson's chi-square test results for employment status, by the presence of at least one priority health condition. Results indicated participants with at least one priority condition were significantly more likely to be unemployed (X^2=4.249, p<.05), and statistically significant differences were also found in terms of categorical groupings of number of missed workdays due to illness (X^2=5.222, p<.05).

Table 10. Crosstabs of employment characteristics (N = 648)

Variable name	No Physical Condition N(%)	Physical Condition N(%)
Employment Status	X^2=4.249*	
Employed	48 (40.7%)	159 (30.8%)
Unemployed	70 (59.3%)	357 (69.2%)
Number of missed workdays due to illness/injury[1]	X^2=5.222*	
0 days	36 (47.4%)	95 (38.3%)
1-5 days	23 (30.3%)	59 (23.8%)
6-10 days	6 (7.9%)	29 (11.7%)
11-15 days	2 (2.6%)	15 (6.0%)
16-20 days	4 (5.3%)	16 (6.5%)
21 days or more	5 (6.6%)	34 (13.7%)

Note. Number of missing not included in the calculation of number, percent, or mean. Bivariate differences between those with and without SMI calculated using Pearson's Chi-Square or Independent Sample t-test, as appropriate. Employment data based on information collected during the final round of data collection.
* p<.05, **p<.01, ***p<.001
[1]Reflects the number of missed workdays during the entire survey period, for those employed at any time during the survey period (n=324). Due to ordinal nature of the variable, an ordinal chi-square (linear-by-linear association) test was used.

Independent t-test results (see table 11) also indicated that participants who were unemployed at the end of the survey period had a higher mean number of priority health conditions (*M* = 3.10, vs. *M* = 1.92).

Table 11. Independent t-test of number of number of priority health conditions, by employment status (n=634)

Variable name	Employed $\bar{x}$	Unemployed $\bar{x}$	t
#Priority Conditions	1.92	3.10	7.362***

Note. Reflects employment status in round five, and number of priority health conditions in round one.
* p<.05, **p<.01, ***p<.001

Table 12 displays independent t-test results of the number of workdays employed participants missed due to illness, by the presence of at least one priority health condition. Results indicated participants with at least one priority health condition, who were employed at any point during the survey period, missed significantly more workdays due to illness or injury over the course of the survey period (t= -2.439, p<.05). Notably, no significant correlation was found between number of priority health conditions and number of missed workdays due to illness or injury (r = -.003, p = .958). These results provide support for hypotheses 3.1 and 3.2 at the bivariate level, with the exception of the relationship between number of priority conditions and missed workdays.

Table 12. Independent t-test of number of missed work days due to illness/injury, by presence of priority health condition (n=324)

Variable name	No Priority Condition $\bar{x}$	Priority Condition $\bar{x}$	t
#Missed workdays	5.57	10.42	-2.439*

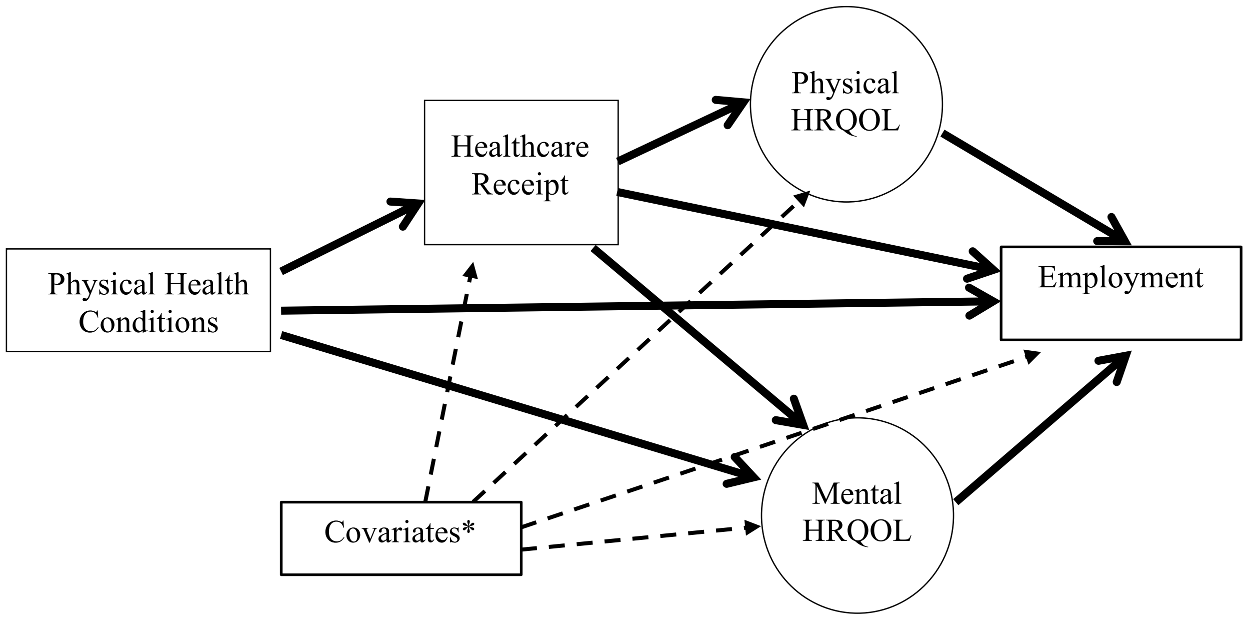
Note. Reflects the number of missed workdays during the entire survey period, for those employed at any time during the survey period (n=324). A log-transformed version of this variable was used due to severe violations to normality. Means reflect non-transformed values.
* p<.05, **p<.01, ***p<.001

Path Model

A path model controlling for sex, race/ethnicity, age, health insurance status, and disability receipt was fit to the data. The path model posited that receipt of healthcare, physical

HRQOL, and mental HRQOL would partially mediate the relationship between chronic physical health conditions and employment (see figure 9).

Figure 9. Path model



*Model controls for sex, race/ethnicity, age, health insurance, education, and disability receipt.

Two separate theoretical models were fit to the data to examine research questions four, five, and six. The first SEM model included the binary AHRQ priority health condition variable, and the second model included a continuous variable that indicated the number of AHRQ priority health conditions an individual reported. Additionally, each model was analyzed two ways: 1) with survey weights and the Sobel method to test indirect effects, and 2) without survey weights with BC bootstrapped confidence intervals used to test indirect effects. Procedures for analyzing both models, which included a binary outcome (employed/unemployed), were informed by Muthén and Asparouhov (2015), and Muthén and Muthén (2017); WLSMV was used as the estimator for the full SEM analyses.

Probit regression coefficients are reported for relationships involving a categorical outcome (i.e., employment), while linear regression coefficients are reported for relationships with a continuous outcome (i.e., healthcare receipt and HRQOL). As noted previously in the methodology section, probit estimates with a binary outcome cannot be meaningfully interpreted in the same way that linear or logistic regression coefficients can be. With a binary observed outcome (i.e., employment), a continuous latent variable is automatically computed by Mplus to represent the observed outcome (Muthén & Asparouhov, 2015). When the latent variable exceeds a particular threshold (as computed by the analysis), $y=1$ (e.g. employed) is indicated instead of $y=0$ (e.g., unemployed). Thus, the coefficients for relationships with employment, indicate the change in the continuous latent response variable behind the observed employment status variable, for a one-unit change in the predictor variable. Similarly, indirect effects with employment as the outcome refer to the continuous latent response variable and cannot be interpreted meaningfully. Wald *z* tests were used to test statistical significance among the factor loadings, path coefficients, and indirect effects computed using the Sobel method; an α value of .05 was used to indicate statistical significance. For unweighted analyses that used BC bootstrapped confidence intervals to test indirect effects, statistical significance was indicated if the 95% confidence interval for the specific indirect effect, or the sum of indirect effects for a relationship, did not contain zero (MacKinnon et al., 2004).

Any priority health condition. To test hypotheses 1-5, the full SEM model with a binary priority health condition variable was first fit to the data using the suggested stratification and primary sampling unit survey weights. Then, the same model was analyzed without the survey weights using bias-corrected bootstrapped confidence intervals (2000 bootstrapped samples drawn). General model fit indices were examined for both analysis methods, and were similar between methods. While the chi-square test of model fit suggested poor fit (Weighted $X^2=434.549$, $p<.001$; Unweighted $X^2=528.499$, $p<.001$), good model fit was reflected in the

RMSEA (Weighted RMSEA=.058; Unweighted RMSEA=.066), CFI (Weighted CFI=.97; Unweighted CFI=.978), and TLI (Weighted TLI=.969; Unweighted TLI=.969) fit indices. As was the case with the CFAs, given that the chi-square test penalizes larger sample sizes (Kenny, 2015; Kline, 2016), it is not surprising that the chi-square results for the full SEM models were statistically significant. More importantly, the other measures for general model fit were within acceptable boundaries. Given these results, the specified theoretical model is determined to have acceptable fit with the data.

Given that MEPS recommends that stratification and cluster weights be included in analyses, the weighted path coefficients for the direct effects were used to make conclusions regarding hypothesis testing and are reported on in-text. Factor loadings for the latent factors representing physical HRQOL and mental HRQOL were all statistically significant, and mirrored loadings found in the measurement model, with only very slight differences noted (see appendix A). Differences were similarly noted between the weighted and unweighted models for direct path coefficients, and in some cases differences in statistical significance were found (see appendix B).

Direct effects. Weighted standardized and unstandardized coefficients are provided for the direct effects in table 13. Factor loadings, and path coefficients for the unweighted model, are provided in appendices A and B. Standardized coefficients for relationships that included a binary predictor variable (i.e., priority health condition, sex, race/ethnicity, health insurance, disability receipt), are only standardized in terms of the outcome variable (Muthén & Muthén, 2017). Standardized coefficients for binary indicators reflect the change in standard deviation units of *y*, for a change in *x* from zero to one (Muthén & Muthén, 2017).

Table 13. Direct path coefficients-Any priority health condition, weighted (n=645)

	Unstandardized Coefficient	S.E.	Standardized Coefficient[1]	S.E.
Healthcare Receipt[2]				
Priority Condition	.157***	.044	.366***	.100
Sex	.102**	.035	.238**	.082
Age	.003*	.001	.104*	.045
Health Insurance	.167**	.050	.388**	.114
Education	.026	.016	.070	.043
Race/Ethnicity	-.044	.038	-.101	.087
Disability Receipt	.140**	.043	.325**	.097
Physical HRQOL				
Priority Condition	-.333***	.062	-.753***	.098
Healthcare Receipt[2]	-.192***	.048	-.186***	.036
Sex	-.074*	.037	-.167*	.081
Age	-.005**	.002	-.154**	.049
Health Insurance	.060	.061	.134	.138
Education	.034	.018	.088	.045
Race/Ethnicity	-.026	.035	-.059	.079
Disability Receipt	-.134**	.041	-.301***	.086
Mental HRQOL				
Priority Condition	-.516***	.095	-.222***	.040
Healthcare Receipt[2]	-.317***	.090	-.149***	.042
Sex	-.174*	.084	-.191*	.091
Age	.003	.003	.049	.048
Health Insurance	.134	.143	.146	.156
Education	.079*	.037	.100*	.046
Race/Ethnicity	-.014	.071	-.015	.078
Disability Receipt	-.190*	.076	-.208*	.083
Employment Status				
Physical HRQOL	.829**	.297	.297**	.101
Mental HRQOL	.271*	.118	.200*	.088
Healthcare Receipt[2]	-.246*	.123	-.085*	.043
Priority Condition	.346*	.166	.279*	.135
Sex	.037	.102	.030	.082
Age	.000	.004	-.004	.045
Health Insurance	.089	.175	.072	.141
Education	.234***	.054	.218***	.049
Race/Ethnicity	-.283*	.123	-.229*	.099
Disability Receipt	-.784***	.120	-.633***	.088

Note. Weighted using the stratification and cluster variables provided by the MEPS. Probit regression coefficients provided when employment is the outcome variable. All other coefficients are linear regression coefficients. S.E.=Standard Error. *p<.05, **p<.01, ***p<.001

[1]Relationships with a binary x-variable are standardized only in terms of y.

[2]Healthcare receipt estimates are in terms of the log-transformed variable.

Statistically significant direct effects were found for all variable-relationships depicted in the theoretical path model (priority health condition, healthcare receipt, physical HRQOL, mental HRQOL, and employment). A priority condition was positively related to healthcare receipt and employment, and was negatively related to physical HRQOL and mental HRQOL. Specifically, a priority condition was associated with a .157 increase in healthcare receipt (β = .157, *b* = .366, $p<.001$), a .333 decrease in physical HRQOL (β = -.333, *b* = -.753, $p<.001$), and a .516 decrease in mental HRQOL (β = -.516, *b* = -.564, $p<.001$). Further, a priority condition was associated with a .346 increase in the continuous latent response variable for employment status (β = .346, *b* = .279, $p<.05$). Priority health conditions had the strongest direct relationship with physical HRQOL, and the weakest relationship with employment status. In the multivariate context, hypotheses 1, 2.1, and 2.2 were supported, but, contrary to bivariate testing, hypothesis 3.1 regarding a negative relationship between a priority condition and employment was not supported.

Healthcare receipt was negatively related to physical HRQOL and mental HRQOL: every one-unit increase in log-transformed healthcare receipt was associated with a .192-unit decrease in physical HRQOL (β = -.192, *b* = -.186, $p<.001$), and a .317-unit decrease in mental HRQOL (β = -.317, *b* = -.149, $p<.001$). In terms of employment, a negative relationship was found for healthcare receipt (β = -.246, *b* = -.085, $p<.05$), and positive relationships were found for physical HRQOL (β = .829, *b* = .297, $p<.01$) and mental HRQOL (β = .271, *b* = .200, $p<.05$). Except for the relationship between healthcare receipt and employment, the relationships between the variables specified in the theoretical model (i.e., healthcare receipt, physical HRQOL, mental HRQOL, and employment) reflected small-to-medium, or medium, effect sizes (Cohen, 1969), and the strongest direct relationship was between physical HRQOL and employment. Results for the direct relationships between physical HRQOL, mental HRQOL and employment provide support for hypotheses 4.4 and 4.5; hypotheses 4.1-4.3, however, are not supported because healthcare receipt had negative relationships with physical HRQOL, mental HRQOL, and employment, opposed to the hypothesized positive relationships.

Predicted probabilities for employment in terms of physical HRQOL, mental HRQOL, and priority health condition are provided in table 14. If physical HRQOL is set at its mean (*M* = -.702), the relationship between physical HRQOL and employment is associated with a -.571 change in z-score. Thus, controlling for covariates, an individual with SMI with -.702 physical HRQOL had a 28% probability of employment. A one standard deviation increase in physical HRQOL was associated with a 39% probability of employment. Taken together, an improvement in physical HRQOL by one standard deviation increased the probability of employment by 11%. Using the same procedures, a one standard deviation improvement in mental HRQOL was associated with an 8% increased probability of employment. Additionally, controlling for all other variables, having at least one priority health condition was directly associated with an increased probability of employment from 46% to 57%, an increase of 11%.

Table 14. Predicted probability of employment

Predictor Variable	Probability at $\bar{x}$	Probability $\bar{x}$ +/- 1SD[1]
Physical HRQOL	28%	39%
Mental HRQOL	41%	49%
	Probability at x=0	Probability at x=1
Priority Health Condition	46%	57%

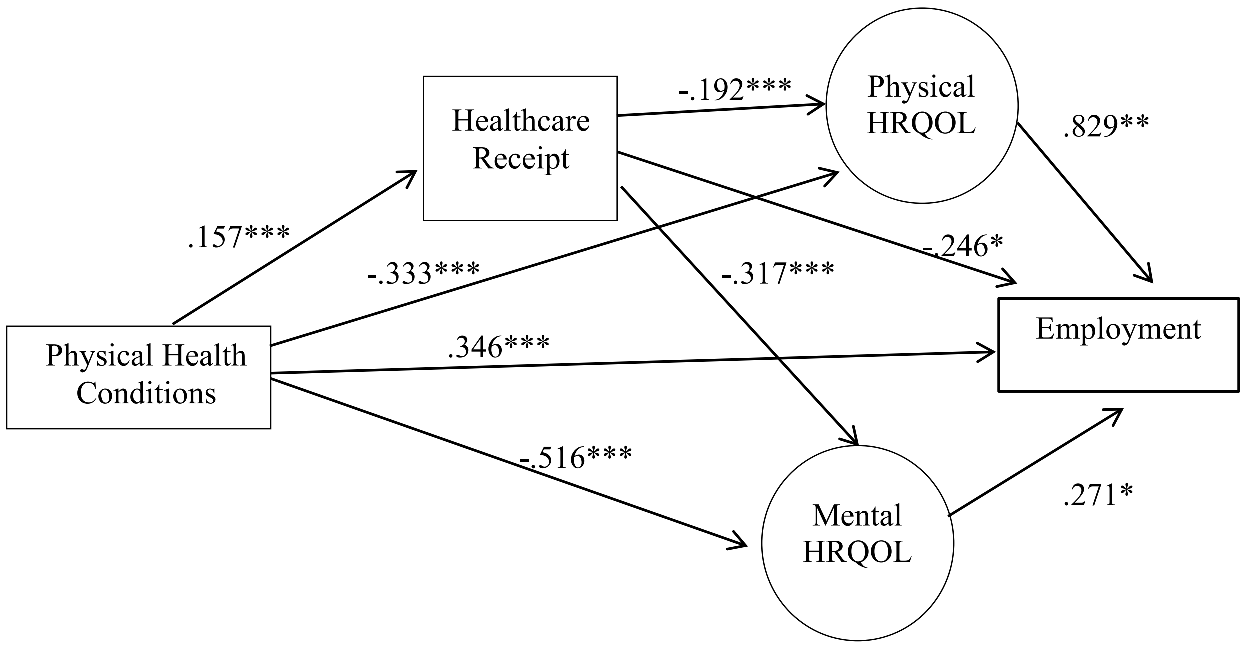
[1] 1SD is added for physical and mental HRQOL; 1SD is subtracted for healthcare receipt.

Statistical significance was also found in many, but not all, covariate relationships (see table 13). Females received more healthcare (β = .102, *b* = .238, $p<.01$), and had lower physical HRQOL (β = -.074, *b* = -.167, $p<.05$) and mental HRQOL (β = -.174, *b* = -.191, $p<.05$). Age was only significantly related to healthcare receipt and physical HRQOL: every one-year increase in age was associated with a .003 increase in healthcare visits (β = .003, *b* = .104, $p<.05$), and with a .005 decrease in physical HRQOL (β = -.005, *b* = -.154, $p<.01$). No relationship was found between sex or age and employment status. Health insurance was only significantly related to healthcare receipt: possession of health insurance was associated with increased healthcare receipt (β = .167, *b* = .388, $p<.01$). Education was positively related to mental HRQOL (β = .079, *b* = .100, $p<.05$) and employment (β = .234, *b* = .218, $p<.001$). Finally, disability receipt was positively related to healthcare receipt (β = .140, *b* = .325, $p<.01$), and negatively related to physical HRQOL (β = -.134, *b* = -.301, $p<.01$), mental HRQOL (β = -.190, *b* = -.208, $p<.01$), and employment (β = -.784, *b* = -.633, $p<.001$). Effect sizes for relationships that include a bivariate covariate (i.e., sex, health insurance, and disability receipt) cannot be compared to the Cohen (1969) standards because only the outcome variable is standardized. In terms of education and age, however, all covariate relationships reflected a small effect size, except for the relationship between education and employment that had a medium effect size (Cohen, 1969). A strong negative relationship was also noted for disability receipt and employment.

Approximately 54% of the variance in employment status (R^2=.541), 29% of the variance in physical HRQOL (R^2=.286), 13% of the variance in mental HRQOL (R^2=.125), and 15% of the variance in healthcare receipt (R^2=.145) was explained by the model. The direct-effect findings provided conflicting support for the hypothesized theoretical model, in that the direction of some of the relationships were opposite of those hypothesized based on the health as human capital model (Grossman, 1972) and the behavioral model for health service utilization (Andersen, 1995; Andersen & Newman, 1973). Specifically, the direct relationships between a priority condition and employment, and healthcare receipt and physical HRQOL, mental HRQOL, and employment, were opposite of those hypothesized.

Figure 10 displays the raw direct path coefficients, computed using survey weights, graphically on the theoretical path model.

Figure 10. Unstandardized coefficients for theoretical paths in full SEM model-Any priority health condition, with survey weights



[1]Model controls for sex, race/ethnicity, age, health insurance, education, and disability receipt.
*p<.05, **p<.01, ***p<.001

Indirect effects. Indirect effect estimates (i.e., mediation analyses) using the Sobel method and bias-corrected bootstrapped confidence intervals are contained in tables 15 and 16. Mediation analyses that included priority health condition are standardized in terms of both the outcome variable and mediator(s), but not priority health condition (Muthén & Muthén, 2017). Eight specific indirect effects were tested. Healthcare receipt was only tested as a mediator when physical HRQOL or mental HRQOL was included. While healthcare was significantly related to employment, the effect size was very small, and theory suggests that healthcare improves employment through a change in health status (i.e., HRQOL). Thus, healthcare as a single mediator between a priority health condition and employment was not tested. Weighted analyses that used Sobel testing, and tested significance with Wald-z tests, indicated statistical significance for nearly all specific indirect effects. The only exception was the specific indirect path between a priority condition and employment that included both healthcare receipt and mental HRQOL. Importantly, like the direct effects with employment as the outcome, the estimates provided for indirect effects that included employment are in relation to the latent response variable computed by Mplus, not the observed employment status variable. Unweighted analyses that used BC bootstrapped confidence intervals to test indirect effects indicated that all specific indirect paths were statistically significant, in that no confidence interval contained zero.

Table 15. Indirect effects using Sobel method-Any priority health condition, with survey weights (n=645)

Indirect Paths	Unstandardized		Standardized	
	Estimate	S.E.	Estimate	S.E.
Condition→ Healthcare→ Physical HRQOL	-.030**	.011	-.068**	.022
Condition→ Healthcare→Mental HRQOL	-.050*	.020	-.055*	.022
Condition→ Physical HRQOL→ Employment	-.277**	.100	-.223**	.081
Condition→ Mental HRQOL→ Employment	-.140*	.065	-.113*	.053
Condition→ Healthcare→Physical HRQOL→ Employment	-.025*	.012	-.020*	.010
Condition→ Healthcare→ Mental HRQOL→ Employment	-.014	.008	-.011	.006
Sum of indirect effects Condition →Employment	*-.455****	*.080*	*-.367****	*.066*
Healthcare→ Physical HRQOL→ Employment	-.159*	.065	-.055*	.023
Healthcare→ Mental HRQOL→ Employment	-.086*	.043	-.030*	.015
Sum of indirect effects Healthcare →Employment	*-.245****	*.060*	*-.085****	*.022*

Note. Weighted using the stratification and cluster variables provided by the MEPS. Significance testing completed using Wald-z tests. S.E.=Standard Error. *p<.05, **p<.01, ***p<.001

Table 16. Indirect effects using bias-corrected bootstrapped confidence intervals-Any priority health condition, no survey weights (n=645)

Indirect Paths	Unstandardized		Standardized	
	Est.	95% C.I.	Est.	95% C.I.
Condition→ Healthcare→ Physical HRQOL	-.031	-.064, -.010	-.068	-.131, -.023
Condition→ Healthcare→ Mental HRQOL	-.050	-.103, -.013	-.054	-.113, -.015
Condition→Physical HRQOL→Employment	-.275	-.545, -.076	-.222	-.447, -.064
Condition→Mental HRQOL→Employment	-.145	-.326, -.013	-.117	-.259, -.016
Condition→ Healthcare→ Physical HRQOL→Employment	-.025	-.063, -.006	-.020	-.052, -.005
Condition→Healthcare→ Mental HRQOL→Employment	-.014	-.040, -.001	-.011	-.033, -.001
Sum of indirect effects Condition →Employment	*-.458*	*-.656, -.298*	*-.370*	*-.543, -.246*
Healthcare→ Physical HRQOL→ Employment	-.158	-.346, -.044	-.055	-.120, -.017
Healthcare→ Mental HRQOL→ Employment	-.087	-.225, -.011	-.030	-.080, -.004
Sum of indirect effects Healthcare→ Employment	*-.244*	*-.395, -.124*	*-.085*	*-.138, -.044*

Note. Statistical significance is indicated if the 95% confidence interval (C.I.) does not include zero.

The indirect effect of a priority condition on physical HRQOL suggested that the addition of healthcare receipt as a mediator accounted for approximately 8% of the total effect (i.e., sum of direct effect and indirect effects), suggesting partial mediation. Healthcare receipt also partially mediated the relationship between a priority condition and mental HRQOL (approximately 9% of the total effect). The indirect effect of healthcare receipt on employment included two parallel mediators (physical HRQOL and mental HRQOL), and partial mediation was indicated. The specific indirect path that included physical HRQOL accounted for approximately 32% of the total effect, and the path that included mental HRQOL accounted for approximately 18% of the total effect. Notably, while the direct effect of a priority condition on employment indicated that a priority condition increased employment, mediation analyses indicated that that a priority condition was negatively related to employment. The total effect of a priority condition on employment was -.109 in both weighted and unweighted analyses. The addition of the mediators reversed the direction of the relationship between a priority condition and employment, suggesting inconsistent mediation (MacKinnon, Krull, & Lockwood, 2000).

The vast majority of this change in relationship was due to the indirect path that included physical HRQOL only (approximately 60% of the sum of the indirect effect) and mental HRQOL only (approximately 31% of the sum of the indirect effect). Given that BC bootstrapped confidence intervals are preferable for testing indirect effects (MacKinnon et al., 2004), statistically significant mediation was indicated for all specific indirect paths, providing support for hypotheses 5.1- 5.8. However, given that BC bootstrapped confidence intervals do not allow for the inclusion of survey weights, the null hypothesis of 5.8 regarding the indirect path that included priority health condition, healthcare receipt, mental HRQOL, and employment is very cautiously rejected.

Number of priority health conditions. To test hypotheses 1-4 and 6, the full SEM model with the continuous priority health condition variable was tested in the same procedures discussed above. The chi-square test of model fit again suggested poor fit (Weighted X^2=425.5854, $p<.001$; Unweighted X^2=528.499, $p<.001$), however good model fit was reflected in the RMSEA (Weighted RMSEA=.057; Unweighted RMSEA=.066), CFI (Weighted CFI=.976; Unweighted CFI=.978), and TLI (Weighted TLI=.967; Unweighted TLI=.969) fit indices. Given these results, the specified theoretical model is determined to have acceptable fit with the data.

As noted previously, probit regression coefficients are reported for relationships involving a categorical outcome (i.e., employment), while linear regression coefficients are reported for relationships with a continuous outcome. Additionally, standardized estimates for relationships involving a binary covariate are only standardized in terms of the outcome variable.

Direct effects. The weighted direct path coefficients are provided in table 17. Factor loadings and path coefficients for the unweighted model are provided in appendices C and D.

Table 17. Direct path coefficients-Number of priority health conditions, weighted (n=645)

	Unstandardized Coefficient	S.E.	Standardized Coefficient[1]	S.E.
Healthcare Receipt[2]				
Priority Condition	.047***	.008	.247***	.042
Sex	.084*	.033	.194*	.076
Age	.001	.002	.038	.048
Health Insurance	.175***	.048	.407***	.109
Education	.032*	.016	.086*	.042
Race/Ethnicity	-.047	.037	-.108	.086
Disability Receipt	.116**	.043	.270**	.098
Physical HRQOL				
Priority Condition	-.089***	.015	-.448***	.036
Healthcare Receipt[2]	-.136**	.040	-.130***	.034
Sex	-.053	.034	-.118	.073
Age	-.001	.002	-.036	.051
Health Insurance	.025	.057	.055	.127
Education	.019	.017	.050	.044
Race/Ethnicity	-.012	.037	.026	.082
Disability Receipt	-.104*	.042	-.231*	.092
Mental HRQOL				
Priority Condition	-.123***	.019	-.299***	.044
Healthcare Receipt[2]	-.249**	.091	-.115**	.042
Sex	-.157	.082	-.169	.088
Age	.008*	.004	.119*	.051
Health Insurance	.077	.136	.083	.147
Education	.062	.037	.077	.046
Race/Ethnicity	.017	.074	.019	.079
Disability Receipt	-.150	.081	-.162	.087
Employment Status				
Physical HRQOL	.696*	.307	.243*	.103
Mental HRQOL	.289*	.120	.208*	.087
Healthcare Receipt[2]	-.242	.129	-.081	.043
Priority Condition	-.034	.041	-.061	.071
Sex	.041	.104	.032	.081
Age	.003	.005	.030	.049
Health Insurance	.117	.184	.091	.143
Education	.236***	.055	.212***	.048
Race/Ethnicity	-.340**	.128	-.264**	.098
Disability Receipt	-.796***	.122	-.618***	.088

Note. S.E.=Standard Error. *p<.05, **p<.01, ***p<.001

Weighted using the stratification and cluster variables provided by the MEPS. Probit regression coefficients provided for relationships where employment is the outcome variable. All other coefficients are linear regression coefficients.

[1]Relationships with a binary x-variable are standardized only in terms of y.

[2]Healthcare receipt estimates are in terms of the log-transformed variable.

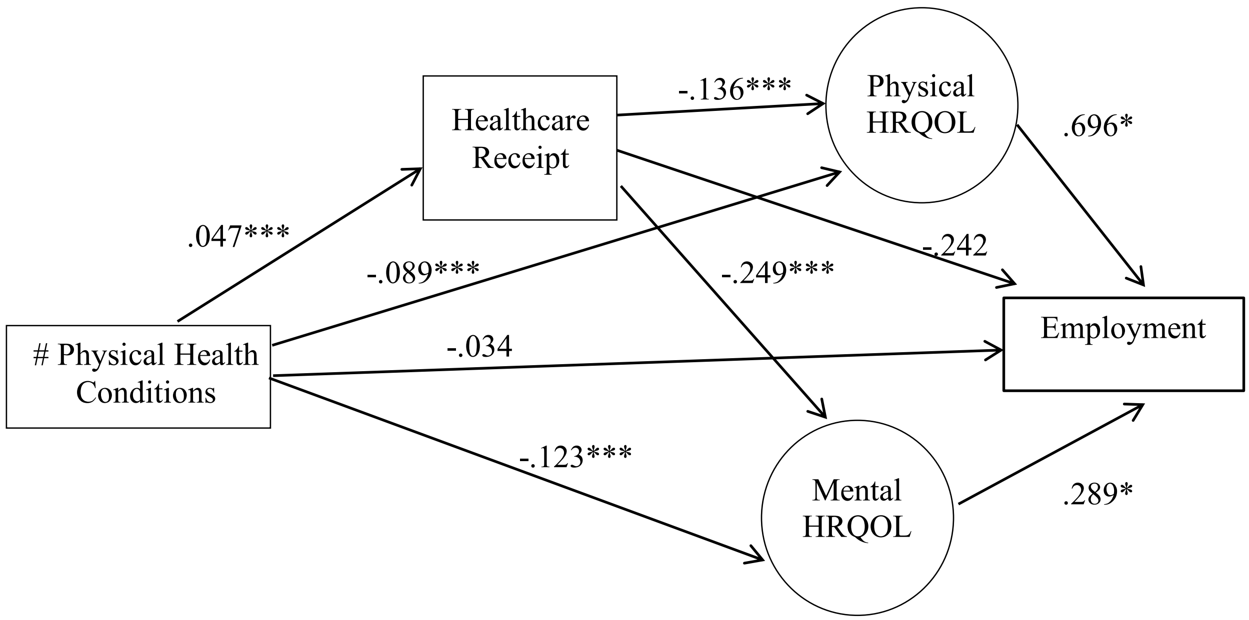
Unlike the model that included a binary priority health condition variable, not all hypothesized direct paths were statistically significant. Number of priority health conditions had statistically significant direct effects on healthcare receipt (β = .047, *b* = .247, $p<.001$), physical HRQOL (β = -.089, *b* = -.448, $p<.001$), and mental HRQOL (β = -.136, *b* = -.130, $p<.01$), but not on employment ((β = .-034, *b* = -.061, p=.399). The standardized coefficients reflected a large effect size for number of priority conditions in terms of physical HRQOL, a medium effect size for healthcare receipt, and a small effect size for mental HRQOL (Cohen, 1969). Similar to the binary health condition model, hypotheses 1, 2.1, and 2.2 were supported, but hypothesis 3.1 regarding a negative direct relationship between a priority condition and employment was not supported.

In agreement with the prior model with the dichotomous priority health condition variable, healthcare receipt had a small (Cohen, 1969), negative, relationship with physical HRQOL (β = -.136, *b* = -.130, $p<.01$) and mental HRQOL (β = -.249, *b* = -.115, $p<.05$). No statistically significant direct effect was found for the relationship between healthcare receipt and employment. Positive relationships, with a medium effect size (Cohen, 1969), however, were found for physical HRQOL (β = .626, *b* = .243, $p<.05$) and mental HRQOL (β = .289, *b* = .208, $p<.05$), in terms of employment. An individual with physical HRQOL equal to the mean (*M* = -.471) had a 32% probability of employment, while an individual with physical HRQOL one standard deviation (*SD* = .448) above the mean had a 58% probability of employment. Similarly, an individual with mental HRQOL equal to the mean (*M* = -.270) had a 39% probability of employment, compared to a 48% probability of employment for an individual with mental HRQOL one standard deviation (*SD* = .927) above the mean. Thus, controlling for all other variables, a one standard deviation increase in physical HRQOL increased probability of employment by 26%, and a one standard deviation increase in mental HRQOL increased probability of employment by 9%. Results for the relationships between physical HRQOL, mental HRQOL, and employment provide further support for hypotheses 4.4 and 4.5, and hypotheses 4.1-4.3 regarding positive relationships for healthcare receipt with physical HRQOL, mental HRQOL, and employment, remain unsupported.

Statistical significance was again found for several covariate relationships (see table 17), however results differ substantially from the binary priority health condition model. Females received more healthcare (β = .084, *b* = .194, $p<.05$), however different from the binary model, statistically significant relationships were not found in terms of physical HRQOL and mental HRQOL. Age was only significantly related to mental HRQOL, and health insurance was only related to healthcare receipt (β = .175, *b* = .407, $p<.001$). Again, notably, no relationship was found between sex or age and employment status. Education was positively related to healthcare receipt (β = .032, *b* = .086, $p<.05$) and employment (β = .236, *b* = .212, $p<.001$), and race/ethnicity was only significantly related to employment status (β = -,340 *b* = -.264, $p<.001$). Finally, disability receipt was positively related to healthcare receipt (β = .116, *b* = .270, $p<.01$), and negatively related to physical HRQOL (β = -.104, *b* = -.231, $p<.05$), mental HRQOL (β = -.150, *b* = -.162, $p<.05$), and employment (β = -.796, *b* = -.618, $p<.001$). The differences between the two models in terms of covariate relationships is seemingly due to the change in measurement of priority health conditions: a continuous number of priority health conditions, versus a binary indicator.

Approximately 54% of the variance in employment status (R^2=.544), 34% of the variance in physical HRQOL (R^2=.342), 15% of the variance in mental HRQOL (R^2=.146), and 17% of the variance in healthcare receipt (R^2=.172) was explained by the model. The direct-effect findings again provided conflicting support for the hypothesized theoretical model, in that the relationships between healthcare receipt and physical HRQOL, and mental HRQOL, were opposite of those hypothesized. Direct path coefficients are depicted graphically in figure 11.

Figure 11. Unstandardized coefficients for theoretical paths in full SEM model-Number of priority health conditions, with survey weights



[1]Model controls for sex, race/ethnicity, age, health insurance, education, and disability receipt.
*p<.05, **p<.01, ***p<.001

Indirect effects. Indirect effect estimates are provided in table 18 and 19. Procedures for testing indirect effects (i.e., mediation) matched those used for the prior model. Weighted analyses indicated statistically significant specific indirect effects for priority health conditions on physical HRQOL and mental HRQOL, through healthcare receipt, and for priority conditions on employment through physical HRQOL or mental HRQOL (see table 18). In the weighted analyses, non-significant specific indirect effects were found for healthcare receipt on employment (through physical HRQOL, p = .051; mental HRQOL, p = .058), and for priority conditions on employment that included serial mediation through healthcare receipt and physical HRQOL (p = .073) or mental HRQOL (p = .067). However, unweighted analyses that used BC bootstrapped confidence intervals to test indirect effects indicated statistical significance for all specific and summed indirect effects, except for the specific indirect effect of priority health conditions on employment through healthcare receipt and mental HRQOL (see table 19).

Table 18. Indirect effects using Sobel method-Number of priority health conditions, with survey weights (n=645)

Indirect Paths	Unstandardized		Standardized	
	Estimate	S.E.	Estimate	S.E.
Condition→ Healthcare→ Physical HRQOL	-.006**	.002	-.032**	.010
Condition→ Healthcare→ Mental HRQOL	-.012*	.005	-.028*	.012
Condition→ Physical HRQOL→ Employment	-.062*	.027	-.109*	.047
Condition→ Mental HRQOL→ Employment	-.035*	.016	-.062*	.028
Condition→ Healthcare→ Physical HRQOL→ Employment	-.004	.002	-.008	.004
Condition→ Healthcare→ Mental HRQOL→ Employment	-.003	.002	-.006	.003
Sum of indirect effects Condition →Employment	*-.105****	*.019*	*-.184****	*.035*
Healthcare→ Physical HRQOL→ Employment	-.095	.048	-.032	.016
Healthcare→ Mental HRQOL→ Employment	-.072	.038	-.024	.013
Sum of indirect effects Healthcare →Employment	*-.166***	*.053*	*-.056***	*.018*

Note. Weighted using the stratification and cluster variables provided by the MEPS. Significance testing completed using Wald-z tests. S.E.=Standard Error. *p<.05, **p<.01, ***p<.001

Table 19. Indirect effects using bias-corrected bootstrapped confidence intervals-Number of priority health conditions, no survey weights (n=645)

Indirect Paths	Unstandardized		Standardized	
	Est.	95% C.I.	Est.	95% C.I.
Condition→ Healthcare→Physical HRQOL	-.006	-.014, -.002	-.033	-.063, -.011
Condition→ Healthcare→ Mental HRQOL	-.012	-.025, -.002	-.028	-.059, -.006
Condition→Physical HRQOL→Employment	-.060	-.120, -.005	-.105	-.216, -.014
Condition→Mental HRQOL→Employment	-.037	-.074, -.003	-.064	-.129, -.007
Condition→ Healthcare→Physical HRQOL→Employment	-.004	-.013, -.001	-.008	-.023, -.002
Condition→ Healthcare→ Mental HRQOL→Employment	-.003	-.010, 0	-.006	-.018, -.001
Sum of indirect effects Condition →Employment	*-.105*	*-.147, -.068*	*-.184*	*-.260, -.122*
Healthcare→ Physical HRQOL→ Employment	-.095	-.261, -.016	-.032	-.089, -.006
Healthcare →Mental HRQOL→Employment	-.072	-.214, -.010	-.024	-.070, -.003
Sum of indirect effects Healthcare →Employment	*-.167*	*-.302, -.055*	*-.056*	*-.102, -.020*

Note. Statistical significance is indicated if the 95% confidence interval (C.I.) does not include zero.

The addition of healthcare receipt as a mediator for the relationship between number of priority conditions and physical HRQOL accounted for approximately 6% of the total effect, suggesting partial mediation. Partial mediation was also found for healthcare receipt as a mediator for the relationship between number of priority conditions and mental HRQOL (approximately 9% of the total effect). These findings on the relationship between healthcare receipt and HRQOL were consistent with the binary priority condition model. The total indirect effect of number of priority conditions on employment was statistically significant, however in the weighted model (using Sobel testing) only the specific indirect paths of physical HRQOL or mental HRQOL as single mediators were significant. Physical HRQOL as a mediator accounted for approximately 45% of the total effect, and mental HRQOL accounted for approximately 25% of the total effect. In the unweighted model, the specific indirect path between number of priority conditions and employment that specified serial mediation through healthcare receipt and physical HRQOL was statistically significant (using BC bootstrapped confidence intervals), however only accounted for approximately 3% of the total effect. Given that the direct effect of number of priority conditions on employment was small and not statistically significant, healthcare receipt, physical HRQOL, and mental HRQOL may fully mediate the relationship in parallel. The specific indirect effects for healthcare receipt on employment were non-significant in the weighted model (Sobel test), but were significant in the unweighted model (BC bootstrapped confidence intervals). The total indirect effect was statistically significant in both the weighted and unweighted models, and given that the direct effect of healthcare receipt on employment was not statistically significant in either model, physical and mental HRQOL may fully mediate the relationship together as parallel mediators (approximately 41% of total effect). However, given that full (i.e. complete) mediation was not tested, a conclusion of full mediation for the relationship between number of priority conditions and employment, and healthcare receipt and employment, cannot be confirmed, and thus should be tested using a new sample (James, Mulaik, & Brett, 2006). Given that BC bootstrapped confidence intervals are preferable for testing indirect effects due to increased statistical power and the absence of the assumption of a normal distribution (see analysis plan in Chapter 3; MacKinnon et al., 2004), statistically significant mediation was indicated for nearly all tested paths. These results provide support for hypotheses 6.1- 6.7, however the null hypothesis is not rejected for 6.8. However, given that BC bootstrapped confidence intervals do not allow for the inclusion of survey weights, hypotheses 6.5-6.7 are very cautiously accepted.

Summary of Results

Results of this study suggest that chronic physical health conditions are related to healthcare receipt, physical HRQOL, mental HRQOL, and employment, for individuals with SMI. At the bivariate level, relationships were consistent regardless of how physical health conditions were measured (i.e., binary or continuous). However, differences were found when relationships were examined in a multivariate context. Table 20 summarizes the main findings of this study.

Table 20: Summary of findings for research questions

Research Question	Overall Findings	Bivariate Findings	Multivariate Findings
What are the differences in healthcare receipt for individuals with physical health conditions, compared to individuals with SMI only?	Hypothesis 1 supported.	Individuals with at least one physical health condition had a higher mean number of healthcare visits. Number of physical health conditions was positively correlated to healthcare receipt.	The presence of a physical health conditions was positively related to healthcare receipt. Number of physical health conditions was positively related to healthcare receipt.
What are the differences in HRQOL for individuals with physical health conditions, compared to individuals with SMI only?	Hypothesis 2.1 and 2.2 supported.	Individuals with at least one physical health condition had a lower mean PCS (physical HRQOL) and MCS (mental HRQOL). Number of physical health conditions was negatively correlated to PCS (physical HRQOL) and MCS (mental HRQOL).	The presence of a physical health condition was negatively related to physical HRQOL and mental HRQOL. Number of physical health conditions was negatively related to physical HRQOL and mental HRQOL.
What are the differences in employment status and missed days of work due to illness for individuals with physical health conditions, compared to individuals with SMI only?	Hypothesis 3.1 supported at bivariate level, and supported in terms of total effects at multivariate level. Hypothesis 3.2 supported in terms of one or more physical health conditions only.	Individuals with at least one physical health condition had a lower employment rate, and more missed days of work due to illness/injury. Unemployed individuals had a higher number of physical health conditions. Number of physical health conditions was not significantly correlated to number of missed workdays.	The total effect of a physical health condition was negatively related to employment, but the direct effect indicated a positive relationship. Number of physical health conditions was not directly related to employment, but the total effect indicated a negative relationship.

		Multivariate Findings
What are the direct relationships between healthcare receipt, physical HRQOL, mental HRQOL, and employment, for individuals with SMI?	Hypotheses 4.1-4.3 not supported. Hypotheses 4.4 and 4.5 supported.	One or more physical health condition: healthcare receipt was negatively related to physical HRQOL, mental HRQOL, and employment. Physical and mental HRQOL were each positively related to employment. Number of physical health conditions: healthcare receipt was negatively related to physical and mental HRQOL, but not employment. Physical and mental HRQOL were each positively related to employment.
Do healthcare receipt, physical HRQOL, and mental HRQOL mediate relationships between the presence of a chronic physical health condition and employment, for individuals with SMI?	Hypotheses 5.1-5.7 supported. Hypothesis 5.8 cautiously supported.	Healthcare receipt mediated the relationships between presence of a physical health condition and physical or mental HRQOL, when tested using both the Sobel method and bias-corrected bootstrapped confidence intervals. Physical HRQOL and mental HRQOL each independently mediated the relationship between the presence of a physical health condition and employment, when tested using both the Sobel method and bias-corrected bootstrapped confidence intervals. Physical HRQOL and mental HRQOL each independently mediated the relationship between healthcare receipt and employment, when tested using both the Sobel method and bias-corrected bootstrapped confidence intervals. Healthcare receipt and physical HRQOL together mediated the relationship between the presence of a physical health condition and employment when tested using both the Sobel method and bias-corrected bootstrapped confidence intervals. Healthcare receipt and mental HRQOL together mediated the relationship between the presence of a physical health condition and employment when tested using bias-corrected bootstrapped confidence intervals only. Healthcare receipt, physical HRQOL, and mental HRQOL, in parallel, mediated the

		relationship between a physical health condition and employment.
Do healthcare receipt, physical HRQOL, and mental HRQOL mediate relationships between number of chronic physical health conditions and employment, for individuals with SMI?	Hypotheses 6.1-6.4 supported. Hypotheses 6.5-6.7 cautiously supported. Hypothesis 6.8 not supported.	Healthcare receipt mediated the relationships between number of physical health conditions and physical or mental HRQOL, when tested using both the Sobel method and bias-corrected bootstrapped confidence intervals. Physical HRQOL and mental HRQOL each independently mediated the relationship between number of physical health conditions and employment, when tested using both the Sobel method and bias-corrected bootstrapped confidence intervals. Physical HRQOL and mental HRQOL each independently mediated the relationship between healthcare receipt and employment, when tested using bias-corrected bootstrapped confidence intervals only. Healthcare receipt and physical HRQOL together mediated the relationship between number of physical health conditions and employment when tested using bias-corrected bootstrapped confidence intervals only. Healthcare receipt and mental HRQOL together did not mediate the relationship between number of physical health conditions and employment when tested using either the Sobel method or bias-corrected bootstrapped confidence intervals. Healthcare receipt, physical HRQOL, and mental HRQOL, in parallel, mediated the relationship between number of physical health conditions and employment.

Chapter 5: Discussion

Theory suggests that health is related to employment (Grossman, 1972), and that people use healthcare to improve their health (Andersen, 1995; Grossman, 1972; Solar & Irwin, 2010). To date, much of the existing research on health and employment for adults with SMI is focused on mental health diagnoses, mental health symptoms, and receipt of mental health care (e.g., Ellinson et al., 2007; Luciano & Meara, 2014; Luo et al., 2010; Tse et al., 2014). Given that people with SMI have high rates of co-occurring physical health conditions (e.g., DeHert et al., 2011), and that co-occurring conditions are related to increased healthcare receipt (e.g., Egede, 2007; Shen et al., 2008) and worse HRQOL (e.g., Salyers et al., 2000), this study was undertaken to examine an important gap in the literature: relationships between physical health, healthcare, and employment. Specifically, this study used a conceptual model informed by empirical and theoretical literature to examine direct and indirect relationships between physical health conditions, healthcare receipt, HRQOL, and employment for adults with SMI. The findings of this study provide partial support for the tested model among individuals with SMI, as well as for the underlying theories (Andersen, 1995; Grossman, 1972; Solar & Irwin, 2010) that helped to form the conceptual model. The sections below discuss the results of this study in the context of prior literature, and in light of its limitations, and provides implications for future research, social work practice, and healthcare policy.

Healthcare and HRQOL for Individuals with Co-Occurring Conditions

To add to the healthcare utilization and HRQOL literature for persons with SMI, this study examined differences in healthcare receipt and physical and mental HRQOL for individuals with co-occurring physical health conditions, compared to individuals with SMI only. As hypothesized, findings from this study indicate that priority health conditions are related to increased healthcare receipt and decreased physical and mental HRQOL, for persons with SMI. Controlling for structural determinants and illness factors that are also related to healthcare receipt (Andersen, 1995; Andersen & Newman, 1973; Solar & Irwin, 2010), individuals with priority health conditions are found to have higher receipt of total healthcare. Higher physician, physician assistant, and emergency department use is also indicated at the bivariate level. These findings are consistent with prior studies that examined healthcare receipt among adults with co-occurring conditions (Egede, 2007; Shen et al., 2008), but by comparing healthcare receipt among persons with SMI and co-occurring physical health conditions to those with SMI only, they present a new dimension from which to consider healthcare receipt among those with SMI.

Findings that indicate priority health conditions are associated with lower physical and mental HRQOL are in agreement with research by Salyers et al. (2000), and add to this body of literature by demonstrating these relationships in a multivariate context. Importantly, the present findings regarding HRQOL communicate a connection between physical and mental health. While the priority conditions included in this study are physical health conditions, the presence of conditions are related not only to lower physical HRQOL, but also lower mental HRQOL. While the theoretical model framing this study does not suggest a direct, causal relationship between health conditions and HRQOL, it is possible that efforts to prevent or eliminate physical health conditions for persons with SMI will not only improve physical HRQOL, but also improve mental HRQOL, and perhaps even the symptoms of their mental health condition.

While covariate relationships are not the focus of this study, covariates were included due to theoretical and empirical relationships with health. Interestingly, the findings suggest that some covariate relationships differ depending on whether priority conditions are measured as a binary or continuous variable. For example, age is related to healthcare receipt in the binary priority condition model, but not in the continuous priority condition model. Also, sex and age are related to physical HRQOL, and sex and education are related to mental HRQOL, only in the binary priority condition model. The change in measurement (from binary to continuous) increased the R^2 value of physical HRQOL by 5%, and mental HRQOL by 2%. The covariate relationship differences found may be related to the increased variance in physical and mental HRQOL accounted for by including the number of priority health conditions reported by a participant, instead of collapsing the information into two restrictive categories (Altman & Royston, 2006). Thus, the continuous priority health condition variable better specified the model, reducing the significance of the covariates. For example, research suggests that older individuals have a greater number of physical health conditions (Fortin et al., 2005). By measuring health conditions on a continuous scale, the relationship between health conditions and age may be better represented, minimizing the confounding relationship of age on physical HRQOL (Altman & Royston, 2006). Measurement research also demonstrates that categorizing a variable, in this case health conditions, increases the risk for a type one error for a continuous predictor, such as age (Austin & Brunner, 2004). These considerations underscore the importance of the choice of measurement in research of this type.

Descriptive information regarding healthcare receipt and HRQOL is informative and adds to our knowledge regarding healthcare and health for adults with SMI. The relationship between healthcare receipt and HRQOL, however, is of particular interest to examine the potential for healthcare to improve health. The health as human capital model (Grossman, 1972), and the behavioral model for health service utilization (Andersen, 1995; Andersen & Newman, 1973), suggest that healthcare improves an individual's health. To this aim, this study examined direct relationships between healthcare receipt and physical and mental HRQOL, as well as whether healthcare receipt mediated relationships between priority health conditions and HRQOL (i.e., indirect relationships). Physical and mental HRQOL are used as measures of health in this study, and positive direct relationships between healthcare and health were hypothesized, as were indirect relationships between priority conditions and HRQOL. Findings support the hypothesized indirect relationships between priority conditions, and physical and mental HRQOL, through healthcare receipt. However, findings regarding direct relationships indicate statistically significant negative relationships between healthcare receipt and physical and mental HRQOL.

The negative relationships found in this study are not completely surprising, given existing empirical and theoretical literature regarding the relationship between healthcare utilization and health. The behavioral model of health service utilization (Andersen, 1995; Andersen & Newman, 1973) proposes that healthcare receipt improves health, but also that poorer health (e.g., more severe illness) is related to greater healthcare utilization. In support of the proposed theoretical relationship between poor health and healthcare utilization, existing empirical research found that lower HRQOL (as measured with the SF-12 or SF-36) was associated with more healthcare use (e.g., Chamberlain et al., 2014; Singh et al., 2005). Additionally, prior research with adults with SMI found that individuals who had two or more health visits, or one or more hospitalization days, in the prior six months had lower physical and mental HRQOL (i.e., SF-12) scores (Salyers et al., 2000). Findings from the current study are in agreement with prior empirical research and support the theorized negative relationship between healthcare utilization and poor health. Thus, it is possible that the SF-12 measure may be acting as a proxy for illness severity in this study. Contradicting theorized relationships between healthcare receipt and HRQOL (e.g., Andersen, 1995; Andersen & Newman, 1973; Grossman, 1972), and existing empirical literature that is consistent with findings from this current study, suggest that the relationship between healthcare utilization and HRQOL, and its measurement, is complex. While findings from this current study do not provide theoretical support regarding the potential for healthcare to improve health (Grossman, 1972), the results provide information about the relationship between healthcare receipt and HRQOL for adults with SMI and extends the work of Salyers et al. (2000) by examining these relationships in a multivariate context.

Taken together, findings from this study add to the literature on healthcare receipt and HRQOL for adults with SMI, by examining relationships between co-occurring physical health conditions, healthcare receipt, and physical and mental HRQOL in a multivariate context. Greater healthcare receipt is often viewed negatively because of the costs associated with more use, but not using healthcare may also be detrimental for individual health, and for efforts to reduce healthcare costs, in the event that emergency services are used instead of preventive or maintenance care. Thus, while the combination of SMI and physical health conditions is associated with more healthcare receipt, the increased receipt should not necessarily be viewed negatively. Certainly, additional research on the relationship between healthcare receipt and HRQOL for persons with SMI and physical health conditions is warranted, with attention to other components of healthcare use (e.g., reason, quality, diagnosis-specific use standards) that may promote improved health.

Connections between Health and Employment for Individuals with SMI

Consistent with the existing literature (e.g., Luciano & Meara, 2014), a high rate of unemployment is found in the sample of individuals with SMI in the current study. Employment rates are fairly consistent at both the beginning and end of the survey, with approximately 30%

of participants reporting employment. A majority of unemployed participants reported that they were unable to work due to their illness or disability (69.9%), providing descriptive support for the relationship between health and employment in this population.

The current study examined relationships between health conditions, healthcare, HRQOL and employment for adults with SMI, using a conceptualization informed by the health as human capital model regarding the relationship between health and employment (Grossman, 1972). Consistent with prior research (e.g., Chirikos & Nestel, 1985; Ettner et al., 1997), results of this study suggest that an individual's health is related to their employment status, both in terms of diagnosed physical health conditions and physical and mental HRQOL. Bivariate analyses provided support for hypotheses 3.1 and 3.2: The presence of at least one co-occurring physical health condition is associated with unemployment and more missed workdays due to illness, and unemployed participants have a higher mean number of priority health conditions, respectively. Results also point to relationships between the health-related variables and employment status at the multivariate level.

In terms of the connection between health and employment, the most important findings from this study relate to the multivariate relationships that include physical and mental HRQOL. Controlling for priority condition status, sex, age, race/ethnicity, education, health insurance, and disability receipt, physical HRQOL and mental HRQOL were each directly related to employment status for the full sample of adults with SMI; and physical HRQOL had a stronger relationship with employment compared to mental HRQOL. Additionally, physical and mental HRQOL mediated the relationship between priority health conditions and employment, for both the binary and continuous priority health condition models, and physical HRQOL accounted for the greatest percentage of the total indirect effect. These findings advance an understanding of important components of health that may improve employment for individuals with SMI, as well as specifically for people with SMI and co-occurring physical health conditions. Even when controlling for priority health condition status, physical HRQOL was a better predictor of employment than mental HRQOL, stressing the importance of physical health to employment for individuals with SMI. Additionally, it seems that physical health conditions in and of themselves are not the best indicator of health-related employment barriers for persons with SMI; instead, comprehensive measures of health, such as HRQOL, are important predictors of employment. Thus, programs aimed at improving employment should assess for HRQOL, not just diagnosed health conditions, and policy interventions and programs should focus on improving HRQOL. Additional research is needed to understand the primary predictors of physical and mental HRQOL in this population, to identify possible mutable factors on which to focus intervention.

Structural and illness severity determinants, covariates in this study, are also related to employment, and are important to consider given that adults with SMI are a marginalized population. It is not surprising that education, race, and disability receipt are significantly related to employment in the current study, consistent with the theoretical (Grossman, 1972) and empirical (Bureau of Labor Statistics, 2017a, 2017b, 2017d; Kahn, 1998) literature on employment, and that individuals are awarded SSI or SSDI due to a determination of their inability to work due to disability. However, no relationships between sex or age and employment were found, in contrast to prior research. Age is generally negatively related to employment (Bureau of Labor Statistics, 2017c), thus a finding of no relationship may be due in part to excluding individuals older than 70 years of age from the sample. While sex and race were not significantly related to employment status in this current study, the relationship between health and employment may differ for men and women (Chirikos & Nestel, 1985; Ettner et al., 1997; Kahn, 1998; Luo et al., 2010), and for those of differing racial and ethnic identities (Chirikos & Nestel, 1985). It may be that sex or race/ethnicity moderate relationships between health and employment for adults with SMI and future research should examine these relationships.

Theoretical Support

This study examined whether physical health conditions, healthcare receipt, and HRQOL were directly related to employment, and each other, as well as whether healthcare and physical and mental HRQOL mediated relationships between diagnosed physical health conditions and employment. Taken together, results from this study provide partial support for the health as human capital model (Grossman, 1972). Results provide support for relationships between good health (i.e., HRQOL) and employment, both for the entire sample of adults with SMI (i.e., direct effects), and for those who had one or more priority physical health conditions (i.e., indirect effects). Additionally, healthcare receipt, physical HRQOL, and mental HRQOL together mediated the relationship between physical health conditions and employment in parallel (i.e., total indirect effect). This study however, did not substantiate positive relationships between healthcare receipt, and health (i.e., HRQOL) and employment. Instead, this study found negative relationships between healthcare receipt and physical and mental HRQOL, providing support for the behavioral model for health service utilization (Andersen, 1995; Andersen & Newman, 1973), in that individuals who are in worse health (e.g., more severe illness) use more healthcare. Additional research is needed that closely examines healthcare receipt for this population, with careful consideration to the measurement and timing of data collection for the variable, to further examine the health as human capital model in terms of physical health and employment for adults with SMI.

Limitations and Implications for Future Research

Limitations. While this study adds to the literature on health and employment for individuals with co-occurring conditions, it is not without limitations. Data were collected via self-report from the survey participants, including health diagnoses and healthcare utilization data which were not confirmed by a physician or medical record, and employment details which were not confirmed by the employer. Additionally, the full sample of individuals with SMI was included as a single group in analyses, thus differences between mental health conditions could not be examined. Importantly, while a theoretical model was tested, and data collection for the variables reflected some temporal ordering, this study does not establish causal links between the variables. This study did not include a true longitudinal design that accounts for changes in employment or health over time or consider other important aspects of an individual's health such as symptom severity or the presence of co-occurring substance abuse. Further, the time periods between data collection points for the variables may not have been long enough to detect a relationship or may not accurately reflect the strength of the relationship, which could affect reliability of the results. Relatedly, it is important to note that this study examines unidirectional relationships proposed by Grossman's (1972) model. However, the available theoretical and empirical literature also provide support for relationships between healthcare utilization, HRQOL, and employment, in the opposite direction. Bidirectional relationships may exist between HRQOL and healthcare utilization, and HRQOL and employment, thus a limitation of this study is the underlying assumption that relationships are unidirectional.

The time periods between the measurement of healthcare receipt and HRQOL were very short in the current study, and it may be that the time between measurements was too short to observe the health improvements that were hypothesized to occur due to receiving healthcare.

Further, the healthcare receipt data used in this study does not provide details regarding the primary reason for the healthcare visit. People use healthcare for a variety of reasons (e.g., prevention, chronic condition management, acute injuries), and it is not possible with the current study to detect the purpose of participant healthcare visits. Thus, healthcare receipt may include usage due to acute illnesses or injuries unrelated to priority health conditions. Further, the healthcare receipt measure included four sources of healthcare, however participants may have received healthcare from other unspecified sources (e.g., non-traditional healers, inpatient hospitalization). Also, there are healthcare system factors that are related to healthcare access and utilization, but these factors were not part of the dataset. These systems factors are important to capture in future research.

The current study is also limited in terms of choice and measurement of included covariates. While covariates were carefully selected and included because of strong theoretical and empirical research that suggested relationships with the mediating and outcome variables, other factors related to these variables are not represented in the tested model. For example, social support factors, such as marital status, may also be related to employment for individuals with co-occurring conditions. It is also important to note that categorical covariates were dichotomized due to statistical power concerns, as well as low percentages of participants in some categories. Notably, this study dichotomized race/ethnicity to reflect structural distributions of power (i.e., white vs. non-white), but this measurement method does not reflect differences that likely exist between non-white categories.

Future research. The current study tests mediating relationships and importantly, the results of this study point to the need to further examine the relationships. The models examined in this study tested partial mediation, meaning that a direct effect between the predictor and outcome was hypothesized. Findings, however, suggest that HRQOL may completely mediate the relationship between the number of physical health conditions and employment (i.e., no direct effect). Given this, future research should test a complete mediation model for this relationship (James et al., 2006). Additionally, it is important that future research identifies for whom relationships between healthcare, health, and employment are particularly strong or weak, as well as healthcare factors (e.g., setting, type, reason for healthcare receipt, etc.), that have the strongest relationship with future health and employment.

Further examination of the relationship between healthcare receipt and physical and mental HRQOL is important. Research that includes the reason for healthcare receipt (e.g., preventive vs. acute care), healthcare system factors, and longer time periods between measurement points, should be pursued to better understand the nature of relationships between healthcare, HRQOL, and employment. It might also be helpful to examine the reverse relationship between HRQOL and healthcare receipt (e.g., HRQOL as a proxy for illness severity and predictor for healthcare receipt), following consideration of the measurement/timing of healthcare receipt and HRQOL.

It is well known that personal health behaviors (e.g., exercise, chronic disease self-management, and tobacco cessation) are related to health. Relationships between health behaviors, health, and employment should be explored to build a body of research on the relationship between physical health and employment for individuals with SMI. Further, participants included in this study have various mental and physical health diagnoses, and it is possible that relationships differ based on specific mental and physical health conditions (e.g., certain conditions may have a particularly strong negative relationship with HRQOL or employment). Consequently, an examination of relationships between healthcare, HRQOL, and employment for specific mental and physical health conditions, clusters of physical health conditions (e.g., respiratory diseases), as well as highly prevalent mental/physical health condition combinations (e.g., bipolar disorder or schizophrenia, and diabetes [DeHert et al., 2011]) would be useful.

In accord with the social determinants of health framework (Solar & Irwin, 2010), and supported by the behavioral model for health service utilization (Andersen, 1995; Andersen & Newman, 1973), a number of covariates were significantly related to the HRQOL and employment variables. These structural (sex, race/ethnicity, education) and intermediary (health insurance) factors are important determinants of health and require further investigation. An examination of the predicted probabilities of employment given specific covariate responses, e.g., examining and comparing the predicted probabilities at various educational levels, as well as for those belonging to each sex, race/ethnicity, and health insurance category, is warranted. Additionally, the intersectional relationships between these factors can be examined by combining various factors together that are known to be intersectionally related to health and employment (e.g, sex and race/ethnicity). Further, research should more purposefully examine relationships between social determinants, health, and employment. In this study, social determinants and physical health conditions were all exogenous variables, thus, relationships between them were not examined. However, prior research indicates persons with SMI that are female, of low SES, or are minoritized persons of color (e.g., Black or Hispanic), have a higher incidence of physical health conditions (e.g. Cabassa et al., 2013; McEvoy et al., 2005; Razzano et al., 2015). Additional research on relationships between health and employment should consider relationships between gender, SES, race, ethnicity, and health conditions, and examine whether relationships between health and employment differ based on social determinants.

Finally, based upon findings that indicate a strong connection between physical and mental health, intervention research focused on the integration of physical health and healthcare into existing evidence-based practices commonly used in community mental health centers is needed. It may be that enhancing the presence of physical health within interventions that are already in use would not only be effective at improving health and employment for individuals with SMI, but also be efficient given the resource constraints faced by many community mental health centers. For example, research could examine the effectiveness of efforts to integrate physical health into strengths-based case management (Rapp & Goscha, 2011) and individual placement and support (Dartmouth University, 2012) models, and the effectiveness of motivational interviewing (Rollnick, Miller, & Butler, 2008) to improve engagement in physical healthcare for individuals with SMI.

Implications for Social Work Practice

Social workers make up a large percentage of the workforce that provides services to individuals with SMI. Results from this study demonstrate the high incidence of physical health conditions experienced by individuals with SMI, and the connection between physical and mental health. Over 81% of survey participants with SMI had at least one priority health condition and approximately 50% reported three or more priority health conditions. Having a priority health condition was related not only to decreased physical HRQOL, but also to decreased mental HRQOL; and as the number of conditions increased, physical and mental HRQOL decreased. Given the connection between mental and physical health conditions, social workers would be wise to intentionally address the holistic health needs of individuals with SMI, and connect people with the range of health services needed, regardless of the practice setting in which they are providing services (e.g., community mental health center, hospital).

While healthcare models are not the focus of this study, findings regarding the connection between physical and mental health for individuals with SMI provide support for integrated physical and mental healthcare protocols and practices. Integrated healthcare became a priority area of healthcare innovation following the enactment of the ACA (2010), and increased attention has been placed on preparing social workers to work in integrated healthcare settings (e.g., Delva & Ruffolo, 2017; Stanhope & Straussner, 2017). While much attention is on integrating behavioral healthcare (e.g., screening, brief treatment) into primary care settings, less attention has been placed on the integration of primary care into behavioral health settings (e.g., community mental health centers). Co-located physical and mental health services for individuals with SMI may increase the use of preventive and chronic disease management healthcare services, in particular for those who may be hesitant to use healthcare services due to a fear of mental health stigma from other providers (Borba et al., 2012; Galon & Graor, 2012), or physical access barriers. Additionally, non-medical programs and services that can help individuals with SMI to achieve their physical health goals should be offered (e.g., psychoeducation groups), in particular for those with SMI who have been the victims of healthcare provider ignorance and its resulting bias. The strong connections between physical and mental health demonstrated by this study also suggest that assessment and treatment planning processes used within community mental health centers should prominently include physical health.

A well-prepared workforce is key to ensuring the successful integration of physical health with mental health care. The education and training that prepares social workers for practice in integrated healthcare settings must adequately address and build the skills and knowledge needed to work in integrated settings housed within both primary care and community mental health settings. Workforce education and training programs that target knowledge and skill development for integrated healthcare practice (e.g., Behavioral Health Workforce and Educational Training Program [HRSA, n.d.]), provide opportunities for social workers to increase competence and may increase the realization and effectiveness of healthcare integration. Additionally, training and continuing education for social workers practicing in community mental health centers should include the physical health needs of their clients with SMI, as well as the connections between physical health, mental health, and client social and economic outcomes (e.g., employment).

Results of this study demonstrate the connection between health and employment for adults with SMI. Employment is often desired by individuals with SMI (Westcott et al., 2015), is associated with improvements in well-being and life satisfaction (Luciano et al., 2014), reduces dependence on unearned income (Chan et al., 2015; Leddy et al., 2014), and has recently emerged as a condition of health insurance for some (Centers for Medicare and Medicaid Services, 2018a). The findings here emphasize the importance of focusing not only on mental health symptoms and treatment in regards to employment, but also a client's physical health. Innovative practice for integrating physical health, mental health, and employment support may help adults with SMI to achieve their employment goals. For example, it is possible that integrating employment interventions with integrated physical and mental healthcare models could provide improved employment outcomes for individuals with SMI. The findings also have important implications for assessment and treatment planning within employment interventions (e.g., Individual Placement and Support). Simply assessing for physical health conditions in the context of employment-related interventions may not provide the level of detail needed to assist in treatment planning. Instead, employment-related assessments should include unmet physical health and healthcare needs, and a comprehensive view of health, for example physical and mental HRQOL. Additionally, to assist with the integration of physical health into employment interventions, job preparation for clinicians delivering the interventions should include training on assessment and treatment planning strategies related to physical health and healthcare for people with SMI.

Implications for Health Policy

It has long been theorized that good health increases the likelihood of employment, and that quality preventive and acute healthcare services contribute to health improvements (Andersen, 1995; Andersen & Newman, 1973; Grossman, 1972; Solar & Irwin, 2010). While this study does not indicate a positive relationship between healthcare and HRQOL, seemingly due to methodological limitations, the various theoretical and empirical literature suggests this may still be the case. In the U.S., health insurance is the typical method for gaining financial access to formal healthcare services. Thus, it is important that individuals with SMI and co-occurring physical health conditions have access to health insurance, so that they may access formal healthcare. The vast majority of participants in the current study had health insurance, either through public or private sources, but approximately 12% of participants were uninsured. Additionally, in accordance with theory that recognizes health insurance as an enabling factor for health service utilization (Andersen, 1995), results indicated that health insurance was strongly related to healthcare receipt.

Expanding access to health insurance, possibly in part through Medicaid expansion, or through other types of reform (e.g., universal healthcare or a single-payer healthcare system), would reduce barriers to healthcare access for adults with SMI, and may result in improvements in individual health. If good health improves labor market outcomes (e.g., employment), then removing access to healthcare services through the suspension of health insurance coverage may not only be detrimental to an individual's health, but also to their ability to obtain employment. Thus, the authorization of section 1115 waivers that allow states to impose employment / community engagement mandates for Medicaid recipients should be reconsidered (Centers for Medicare and Medicaid Services, 2018a).

Individuals with SMI have low employment rates, difficulties maintaining employment, and are less likely to transition out of unemployment, due to challenges related to mental health symptomology, education, and employer stigma (e.g., Baldwin & Marcus, 2014; Ellinson et al., 2007; Ettner et al., 1997; Lanuza, 2013; Luciano & Meara, 2014; Luo et al., 2010; Stuart, 2006; Tse et al., 2014). Additionally, this study found that poorer physical health decreased the probability of employment for individuals with SMI. Thus, given these health and employment-related challenges, Medicaid policies that include employment mandates would be particularly detrimental for people with SMI. The likelihood of a gap in Medicaid coverage due to unemployment is high, and the results of this study suggest that the coverage gap would be detrimental to individual health and decrease the likelihood of obtaining new employment. Employment mandates may not be effective, or just, for people with mental health conditions, thus states should consider the long-term outcomes of employment mandates in terms of improving health and employment. Those states imposing employment mandates should reconsider sanctions that suspend coverage for individuals with mental health conditions, and instead provide health and employment supports to increase their likelihood for success.

Conclusion

People with SMI experience high rates of chronic physical health conditions, and also low rates of employment. While much research has focused on employment outcomes for people with SMI, little is known about the added burden that physical health conditions may have on the employment efforts of people with SMI. The findings from this study emphasize the importance of physical health on employment status of people with SMI. Siloed methods for delivering healthcare that view mental and physical health as separate entities may not address the complicated health needs of people with SMI, and policies and practices that promote access to integrated and quality healthcare have the potential to improve physical and mental health and employment rates for people with SMI. Given their active presence within both physical and mental healthcare settings, social workers are well-positioned to address the social and behavioral aspects of the complex health needs of adults with SMI. In consideration of the historical, theoretical, public policy, and clinical factors that shaped this research, and by the findings of it, a holistic health approach that equips and empowers adults with SMI to achieve their health and employment-related goals is essential.

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Appendix A
Standardized factor loadings/correlations for binary SEM model

	Weighted[1]		Unweighted	
Variables	Coefficient	S.E.	Coefficient	S.E.
Physical HRQOL				
GH	.419***	.056	.429***	.072
PF1	.791***	.024	.792***	.028
PF2	.800***	.024	.800***	.028
RP1	.926***	.013	.927***	.018
RP2	.960***	.010	.958***	.013
BP	.823***	.020	.818***	.023
Mental HRQOL				
GH	.378 ***	.051	.368***	.071
RE1	.877***	.014	.887***	.018
RE2	.802***	.019	.804***	.026
MH1	.660***	.024	.654***	.038
VT	.755***	.021	.750***	.030
MH2	.783***	.019	.774***	.024
SF	.875***	.015	.873***	.021
PH-MH	.757***	.023	.757***	.029
PF1-PF2	.585***	.044	.584***	.058
RP1-RP2	.121	.134	.132	.227
RE1-RE2	.383***	.043	.365***	.077
MH1-MH2	.184***	.040	.201**	.062

Note. S.E.=Standard Error. *p<.05, **p<.01, ***p<.001
[1]Weighted using the stratification and cluster variables provided by the MEPS.

Appendix B
Unweighted path coefficients for binary SEM model

	Unstandardized		Standardized	
	Coefficient	S.E.	Coefficient	S.E.
Healthcare Receipt[1]				
Priority Condition	.157***	.044	.366***	.101
Sex	.102**	.035	.238**	.074
Age	.003*	.001	.104*	.041
Health Insurance	.167**	.053	.388**	.121
Education	.026	.016	.070	.042
Race/Ethnicity	-.044	.034	-.101	.079
Disability Receipt	.140***	.036	.325***	.082
Physical HRQOL				
Priority Condition	-.344***	.089	-.757***	.118
Healthcare Receipt[1]	-.197**	.060	-.187***	.045
Sex	-.078	.042	-.171*	.086
Age	-.005**	.002	-.150**	.043
Health Insurance	.060	.064	.132	.133
Education	.036	.019	.092	.044
Race/Ethnicity	-.027	.039	-.059	.083
Disability Receipt	-.137**	.047	-.302**	.087
Mental HRQOL				
Priority Condition	-.530***	.115	-.571***	.118
Healthcare Receipt[1]	-.318**	.108	-.148**	.050
Sex	-.176*	.085	-.189*	.090
Age	.003	.003	.046	.045
Health Insurance	.131	.125	.141	.134
Education	.083*	.037	.103*	.046
Race/Ethnicity	-.015	.086	-.016	.092
Disability Receipt	-.188*	.092	-.203*	.097
Employment Status				
Physical HRQOL	.800*	.351	.294**	.112
Mental HRQOL	.273*	.137	.205*	.101
Healthcare Receipt[1]	-.246	.135	-.086	.047
Priority Condition	.349*	.162	.282*	.131
Sex	.038	.115	.031	.092
Age	-.001	.005	-.006	.055
Health Insurance	.091	.169	.074	.135
Education	.232***	.056	.216***	.048
Race/Ethnicity	-.283*	.118	-.229*	.092
Disability Receipt	-.785***	.136	-.634***	.097

Note. S.E.=Standard Error. *p<.05, **p<.01, ***p<.001
Regression coefficients for relationships where employment is the outcome variable are probit; all others are linear. Relationships with a binary x-variable are standardized only in terms of y.
[1]Healthcare receipt estimates are in terms of the log-transformed variable.

Appendix C
Standardized factor loadings and correlations for continuous SEM model

	Weighted[1]		Unweighted	
Variables	Coefficient	S.E.	Coefficient	S.E.
Physical HRQOL				
GH	.417	.056	.408***	.075
PF1	.779***	.026	.775***	.031
PF2	.787***	.025	.781***	.031
RP1	.929***	.012	.932***	.018
RP2	.955***	.011	.955***	.013
BP	.813***	.021	.809***	.024
Mental HRQOL				
GH	.376***	.049	.382***	.073
RE1	.878***	.014	.888***	.018
RE2	.791***	.019	.793***	.028
MH1	.666***	.025	.661***	.037
VT	.734***	.022	.733***	.033
MH2	.800***	.018	.792***	.023
SF	.877***	.014	.876***	.021
PH-MH	.747***	.026	.744***	.030
PF1-PF2	.561***	.046	.566***	.059
RP1-RP2	.172	.121	.139	.208
RE1-RE2	.389***	.042	.375***	.075
MH1-MH2	.175***	.040	.193**	.063

Note. S.E.=Standard Error. *p<.05, **p<.01, ***p<.001
[1]Weighted using the stratification and cluster variables provided by the MEPS.

Appendix D
Unweighted path coefficients for continuous SEM model

	Unstandardized Coefficient	S.E.	Standardized Coefficient	S.E.
Healthcare Receipt[1]				
Priority Condition	.047***	.008	.109***	.018
Sex	.084**	.032	.194**	.073
Age	.001	.001	.038	.043
Health Insurance	.174**	.053	.407**	.122
Education	.032*	.016	.086*	.042
Race/Ethnicity	-.047	.033	-.108	.076
Disability Receipt	.116**	.036	.270**	.082
Physical HRQOL				
Priority Condition	-.085***	.021	-.195***	.021
Healthcare Receipt[1]	-.135*	.053	-.133**	.044
Sex	-.053	.039	-.121	.083
Age	-.001	.002	-.034	.047
Health Insurance	.023	.059	.054	.129
Education	.020	.017	.053	.043
Race/Ethnicity	-.011	.036	-.026	.080
Disability Receipt	-.102*	.043	-.233**	.085
Mental HRQOL				
Priority Condition	-.127***	.021	-.135***	.021
Healthcare Receipt[1]	-.249*	.108	-.114*	.049
Sex	-.153	.085	-.163	.090
Age	.008*	.003	.115*	.048
Health Insurance	.076	.127	.081	.134
Education	.066	.038	.081	.046
Race/Ethnicity	.016	.085	.017	.090
Disability Receipt	-.147	.093	-.156	.097
Employment Status				
Physical HRQOL	.703	.380	.239*	.112
Mental HRQOL	.289*	.138	.211*	.099
Healthcare Receipt[1]	-.241	.138	-.081	.046
Priority Condition	-.035	.034	.027	.026
Sex	.041	.119	.032	.091
Age	.003	.005	.030	.054
Health Insurance	.118	.174	.092	.134
Education	.234***	.058	.210***	.048
Race/Ethnicity	-.340**	.119	-.264**	.089
Disability Receipt	-.797***	.140	-.619***	.097

Note. S.E.=Standard Error. *p<.05, **p<.01, ***p<.001
Regression coefficients for relationships where employment is the outcome variable are probit; all others are linear. Relationships with a binary x-variable are standardized only in terms of y.
[1]Healthcare receipt estimates are in terms of the log-transformed variable.