Walden University

College of Health Sciences and Public Policy

This is to certify that the doctoral study by

Shawanda Pyper Daniel

has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

Review Committee
Dr. Berthline Isma, Committee Chairperson, Public Health Faculty
Dr. Claire Robb, Committee Member, Public Health Faculty

Chief Academic Officer and Provost
Sue Subocz, Ph.D.

Walden University
2023

Abstract

Healthcare Access and Health Equity Outcomes Among Adults With Cardiometabolic Conditions

by

Shawanda Pyper Daniel

MPH, Morehouse School of Medicine, 2001

BS, University of Georgia, 1999

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Public Health

Walden University

November 2023

Abstract

Cardiometabolic diseases such as hypertension, high cholesterol, coronary artery disease, and diabetes collectively are the leading cause of cardiovascular morbidity and mortality in the United States. The purpose of this quantitative cross-sectional study was to analyze the influence of healthcare access (wellness visits and health insurance status), health behaviors (alcohol use and physical activity), and sociodemographic factors (race/ethnicity, sex, age, education, marital status, family job status, and body mass index) on health equity outcomes (health status) in 15,595 adult cardiometabolic National Health Interview Survey (NHIS) 2020 participants. Andersen’s behavioral model (conceptual theory) utilizes sociodemographic (predisposing) factors, healthcare access (enabling) factors, health behavior, cardiometabolic conditions (need), and health status (outcome) for healthcare utilization research. The 2020 NHIS secondary dataset was analyzed to address research questions using binary logistic regression. The results showed that there was a statistically significant relationship between healthcare access, health behaviors, sociodemographic factors, and self-reported health status among adults with collective cardiometabolic conditions in the United States. Physical activity and alcohol use had the highest effect size, demonstrating these key variables as meaningful in predicting health equity represented by health status outcome. Additional research using a longitudinal sample that was collected for the NHIS 2020 for a select group of participants who completed the 2019 and 2020 survey is recommended. This study advances positive social change by providing multiple stakeholders with health equity outcome findings among adults with cardiometabolic conditions.

Healthcare Access and Health Equity Outcomes Among Adults

With Cardiometabolic Conditions

by

Shawanda Pyper Daniel

MPH, Morehouse School of Medicine, 2001

BS, University of Georgia, 1999

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Public Health

Walden University

November 2023

Dedication

All glory, honor, and praise are due to God the Father, God the Son, and God the Holy Spirit. This doctoral study is first dedicated to God for His grace to complete my doctoral program through some challenging personal obstacles. This doctoral study is dedicated to my loving parents, Mr. Cecil Daniel (deceased) and Mrs. Yvonne Elaine Arrington Daniel (retired educator), and my daughter, Kayla Yvonne Johnson. I have always been encouraged to strive for excellence in education and service to others. I pass this legacy on to my daughter. I dedicate my doctoral study work to my maternal and paternal grandmothers (Maggie Andrews Arrington and Pearline Byrd, respectively). My maternal aunts and uncles all wished me well when I started my doctoral journey, but they have all transitioned. My uncle Bobby Arrington told me often that he was very proud of me. My uncle Joseph Arrington reminded me to ensure he received a copy of my master's thesis and my doctoral study work along with encouraging me to be proud of myself. My uncle, the Honorable Marvin Arrington, Sr., blazed a trail of service to community and law to reach judgeship at the highest level in Georgia. My uncle Marvin always told me he was very proud of me and told me I would be successful. My aunt Audrey Arrington demonstrated that you never give up on your dream, and she successfully passed the Georgia bar exam after teaching high school for over 20 years. My aunt Cynthia Arrington Wright (retired school counselor) was always positive and motivating, and she gave me sound advice for this new endeavor. I also dedicate this work to my (late) best friend Lisa A. Feldman for your encouragement, friendship, and loyalty, Dr. K. Harden, Yolanda Longino, and many lifelong friends and relatives.

Acknowledgments

I want to thank my committee chair, Dr. Berthline Isma, for being very supportive, providing excellent feedback and support. This process will challenge you in many ways, but I could always count on my chair to be professional, fair, and very fast with all of my reviews/feedback. I would also like to thank my second committee member, Dr. Claire Robb, for support, encouragement, and challenging me to strive for excellence. I would also like to thank my URR, Dr. Richard Palmer, for his timely responses and expertise. I would like to acknowledge my research alignment and statistics tutor, Dr. Reginald Taylor, for his expertise, encouraging words, and timely responses. I acknowledge my other statistics tutor, Dr. Zin Htway, for the dataset cleaning and statistics help. Thank you, David Kovaz and Zhi Zhou, for helpful discussions. I would like to acknowledge and thank Dr. Michelle Burcin (former DrPH Academic Program Director) for your warm welcome back to the DrPH program. Thank you, Dr. Holly Godwin (Associate Dean for MPH/ DrPH Programs), for your leadership and support. I also acknowledge Dr. Tammy Root for your support.

I acknowledge my entire Arrington and Daniel family. I acknowledge and thank all of my cousins, close friends and associates. I love you all dearly and to God be the Glory!

Table of Contents

List of Tables

List of Figures

Section 1: Foundation of the Study and Literature Review

Introduction

Cardiovascular disease (CVD) is the leading cause of death globally, accounting for 17.9 million deaths in 2020 (World Health Organization [WHO], 2020). The United States lists CVD disparities as the number one cause of death annually (Javed et al., 2022; U.S. Department of Health and Human Services, n.d.). CVD kills one person every 34 seconds, and 697,000 people died from heart disease in 2020 (Centers for Disease Control and Prevention [CDC], 2022c). Health inequity continues to plague society among people with cardiometabolic conditions, and these health burdens must be addressed effectively to achieve better health equity outcomes. Health equity is a state in which everyone should have fair and just opportunity and access to attain the highest level of health, and measuring health equity outcomes is a leading topic among researchers (CDC, n.d.).

Cardiometabolic conditions are cardiovascular and metabolic diseases that contribute individually and collectively to cardiovascular-related deaths. A few examples of common cardiometabolic conditions are coronary heart disease, hypertension, hyperlipidemia, and diabetes (CDC, n.d.). Most cardiometabolic conditions have overlapping risk factors and bidirectional interactions (Cheng et al., 2022). Risk factors for developing cardiometabolic conditions include poor diet, lack of healthcare, obesity, drug use, and other unhealthy behaviors (CDC, 2022d). Healthcare access, health behaviors, and sociodemographic factors influence overall health outcomes, especially for population groups suffering with chronic disease.

This research focuses on adults with cardiometabolic conditions and how health access and health behaviors influence health equity outcomes. This topic is important because improvements in health equity outcomes should lead to improvements for people with cardiometabolic conditions and decrease morbidity and mortality rates. Numerous health organizations, such as the American Heart Association (AHA), Health Resources and Services Administration (HRSA), and CDC, have chosen health equity improvements as a primary goal to reduce health disparities and address preventable illnesses and deaths.

This section focuses on the background of the research study, the problem statement, study purpose, research questions, conceptual framework, nature of the study, definitions, assumptions, scope, limitations, and significance.

Background

Heart disease has been the leading cause of deaths in the United States since the 1950s (Heron & Anderson, 2016). Cardiovascular-related deaths have caused significant social, emotional, and financial burdens within families and nationally. The cost estimates for health disparity are approximately $93 billion in additional medical care costs, $42 billion in loss of productivity per year, and additional economic loss due to premature death costs (Turner, 2018). According to Hamad and Galea (2022), the United States is the only high-income nation that exclusively depends on the healthcare system to address and solve overwhelming disease problems. Health inequity continues today because of an underinvestment in resources and cultural sensitivity to impact social and structural determinants of health (Hamad & Galea, 2022).

Historic origins of health equity research can be traced to the early 1800s, and the WHO endorsed health equity ideals in 1946 (Yao et al., 2019). The United States has disproportionate preventable illnesses due to health inequity, racial disparities, healthcare access issues, and other social determinants of health (SDOH; Kim et al., 2020). Health equity outcomes are key goals for the CDC's Healthy People 2030 in addressing social determinants of health issues such as systemic bias that contributes to health inequity, poor health literacy, and lack of healthcare access (CDC, n.d.). According to Ndugga and Artiga (2021), health equity outcomes are driven by factors such as underlying genetics, social factors, health behaviors, and access to health care, but there is currently no consensus on the weight each contributor may have on health. The researchers further stated that systemic racism and discrimination directly cause health inequities.

Health equity research has increased over the last decade, but there is very little or no literature on analyzing cardiovascular health risk factors, health behaviors, sociodemographic factors, and cardiometabolic conditions (hypertension, cholesterol, coronary heart disease, and diabetes) collectively (Lopez-Neyman et al., 2022). Most studies involve selecting one specific cardiometabolic condition, such as hypertension, cholesterol, coronary heart disease, or diabetes, versus looking at these conditions collectively. My research provided analysis to review health disparities and health inequity within this target group.

Also, despite the numerous frameworks on SDOH, there is no set measurement for health equity. There is no "gold standard" measure for assessing health equity performance, but researchers suggest assessing health equity by preventive care known as wellness visits and health status data (Bailit & Kanneganti, 2022; Cho et al., 2022; Tong et al., 2021). This recommendation aligns with my predictor and outcome variables.

Problem Statement

The specific research problem addressed through this study was the need to analyze health equity outcomes in adults with cardiometabolic conditions against healthcare access, sociodemographic, and health behavior factors using the NHIS 2020 secondary dataset. The NHIS typically occurs every year within the homes of participants, but due to the U.S. national COVID-19 stay-at-home order, the agency conducted mostly phone interviews for most of 2020 (NCHS, 2021). Researchers Ndugga and Galea (2021) reemphasized that there is no consensus on which variables are the best for health equity data capture or measurement; therefore, additional research is needed. According to Cho et al. (2022), life expectancy tables are the most common indicator of mortality; however, self-ratings of health status are more beneficial as a summary metric because they indicate individuals' evaluation of themselves. Even after controlling for health behavior risk, self-reported health status provides a superior review of outcomes.

An extensive literature review did not show that research using the NHIS 2020 dataset has been conducted with the same outcome and predictor variables in adults with cardiometabolic conditions. My research filled the above-mentioned gaps.

Purpose of the Study

The aim of this quantitative, cross-sectional, secondary data analysis was to analyze how my predictor variables of healthcare access (wellness visits and insurance status) and health behaviors (alcohol use and physical activity) influence health equity outcomes (health status) while controlling for sociodemographic factors (race/ethnicity, sex, age, education, marital status, family job status, and body mass index or BMI), among adult cardiometabolic (hypertension, cholesterol, coronary heart disease, and diabetes) NHIS 2020 survey participants.

According to Turner et al. (2022), as data-driven evidence-based medicine increases in importance, researchers must be able to improve health equity outcomes-based research for future public health programming and analysis. The aims of this research is to contribute value-added analysis about underrepresented groups with cardiometabolic illnesses to increase understanding and provide multiple stakeholders information to promote health equity.

Research Questions and Hypotheses

In this study, the research questions were the following:

Research Question 1: To what extent is healthcare access (wellness visits and insurance status) a predictor of the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and body mass index [BMI])?

H_{01}: Healthcare access (wellness visits and insurance status) does not predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI).

H_{A1}: Healthcare access (wellness visits and insurance status) does predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI).

Research Question 2: To what extent are health behavior factors (alcohol use and physical activity) a predictor of the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI)?

H_{02}: Health behavior factors (alcohol use and physical activity) do not predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI).

H_{A2}: Health behavior factors (alcohol use and physical activity) do predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI).

Research Question 3: To what extent are sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI) a predictor of the health equity outcome health status in adults with cardiometabolic conditions in the United States?

H_{03}: Sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI) do not predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States.

H_{A3}: Sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI) do predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States.

Conceptual Framework for the Study

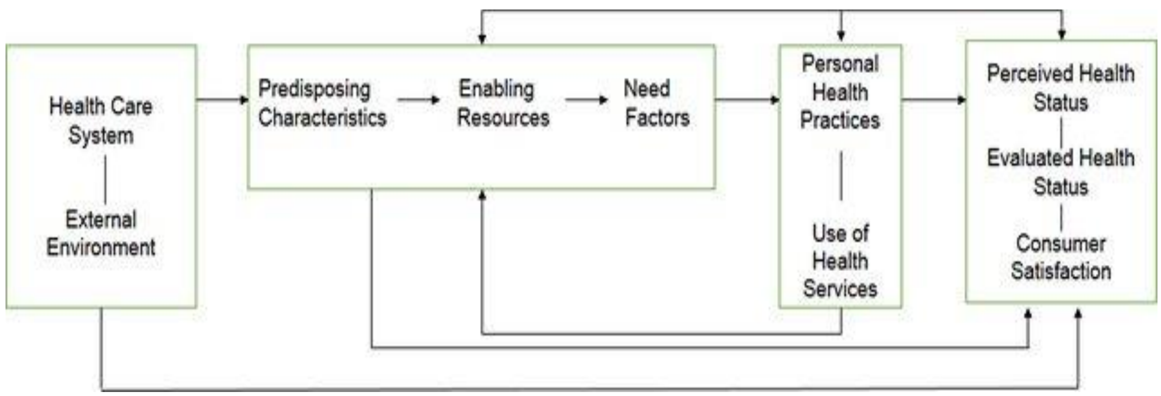
The conceptual framework for this research was grounded in the Andersen behavioral model (ABM), which was developed in 1968 by Ronald M. Andersen, a U.S. medical sociologist and health services expert. The ABM was updated by the original author to Andersen's healthcare utilization model in 1995, and again in 2015 to shift from family-unit-level outcomes to individual-level analysis capturing healthcare utilization and health outcomes (Andersen, 1995; Andersen & Davidson, 2007). The conceptual model addresses predisposing factors, enabling factors, and need factors to encompass contextual, individual health behaviors and outcome characteristics (Lederle et al., 2021). The model focuses on contextual and individual determinants of health such as healthcare access, geographic location, provider health plans, sociodemographic factors, and health behavior and outcome variables (Andersen & Davidson, 2007). The updated version shown in Figure 1 is used often in healthcare utilization research. I have adapted this conceptual framework in Figure 2, to draw attention to the variables of interest by removing the contextual environmental concept. The rationale for selecting this conceptual framework for my research consisted of a set of linked concepts that provide a framework-specific philosophy that is in alignment with my research (Mugizi, 2019). Please see Figure 1 and Figure 2.

The AMB identified the predisposing (sociodemographic) factors, enabling (healthcare access) health behavior factors, need factors (cardiometabolic conditions), and outcomes (health status) that aligned with my research and the NHIS 2020 dataset (Andersen & Davidson, 2007; Lederle et al., 2021). These categories interact, intersect, and are cumulative in shaping one's healthcare experience (Sparks, 2020). The conceptual framework model is not strict and formal, but it represents a less formal way of organizing concepts for contextual understanding post analysis (Mugizi, 2019; Lederle et al., 2021). This framework and its concepts fit well with the health equity outcomes topic, my research problem, and the purpose of the study.

Figure 1

Andersen-Newman Behavioral Model of Health Services Use

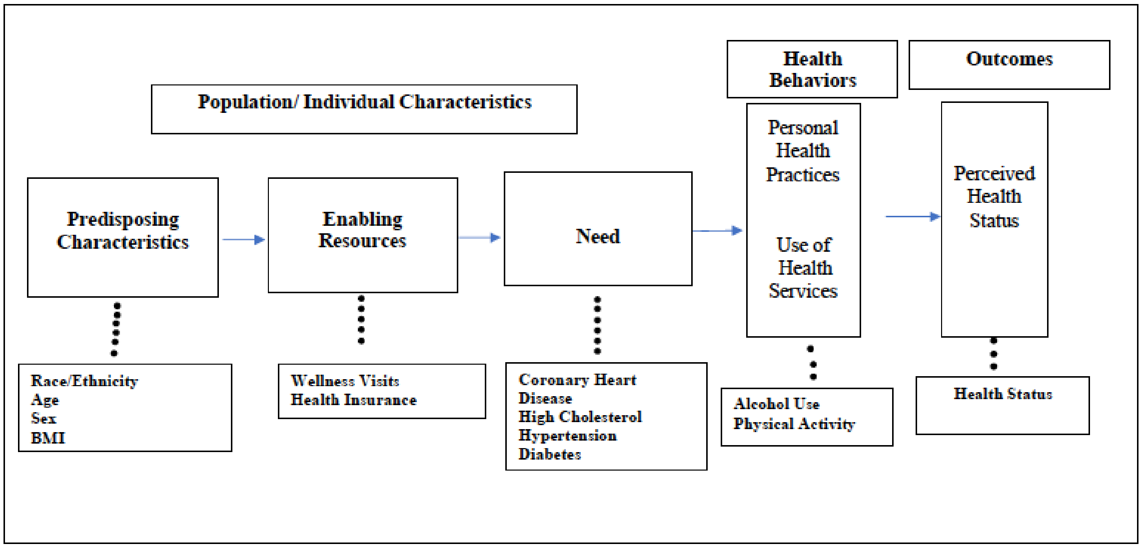
Contextual	**Population Characteristics**	**Health Behavior**	**Outcomes**



Note. Adapted from "Community Perceptions of Community Health Workers (CHWs) and Their Roles in Management for HIV, Tuberculosis and Hypertension in Western Kenya," by B. Rachlis, V. Naanyu, J. Wachira, B. Genberg, B. Koech, R. Kamene, J. Akinyi, and P. Braitstein, 2016, *PLoS One*, 11(2), Article e0149412 (https://doi.org/10.1371%2Fjournal.pone.0149412). Copyright 2016 by Rachlis et al. Open Access Article under Creative Commons Attribution License.

Figure 2

Andersen's Behavioral Model of Health Services Use (Modified for Study Alignment)



Note. Adapted from "Community Perceptions of Community Health Workers (CHWs) and Their Roles in Management for HIV, Tuberculosis and Hypertension in Western Kenya," by B. Rachlis, V. Naanyu, J. Wachira, B. Genberg, B. Koech, R. Kamene, J. Akinyi, and P. Braitstein, 2016, *PLoS One*, 11(2), Article e0149412 (https://doi.org/10.1371%2Fjournal.pone.0149412). Copyright 2016 by Rachlis et al. Open Access Article under Creative Commons Attribution License.

The conceptual framework involved the use of the ABM to review the 2020 NHIS secondary dataset analysis, highlighting the direct correlation to my independent variables, the covariate predisposing factors—sociodemographic variables (race/ethnicity, age, sex, marital status, education, income, job status, and location), the two enabling factors—healthcare access variables (wellness visits and insurance status) and health behavior variables (alcohol use and physical activity), and the outcomes dependent variable of health equity outcome health status in participants with cardiometabolic conditions (need factors).

The ABM has been used in many studies investigating health services outcomes in relation to different chronic diseases (Babitsch et al., 2012). Babitsch et al. (2012) researched studies that included predisposing, enabling, and need factors as self-reported health status in several medical conditions, including CVD, to address outcomes. The summarized results indicate associations between the predictor and outcomes variables within the utilization of care framework. This meta-analysis will be discussed further in the literature review section. The health equity outcome variables selected in my research have been shown to have significance and intersect with other key health predictor variables.

Nature of the Study

In this study, I used secondary data analysis with a cross-sectional study design using binary logistical regression with the NHIS 2020 dataset to analyze my research questions. The public free and validated dataset comprised U.S. adults ages 18 and older and those who were noninstitutionalized as survey participants. The data were analyzed with the Statistical Package for the Social Sciences (SPSS) Version 28. The methodology section and results section will detail descriptive statistics of each variable such as the level of measurement, central tendency, and variation. Detailed analysis and hypotheses results will also be reported.

The NHIS was initiated in 1957 by Congress to monitor the health of the U.S. population (NCHS, 2021, 2022). The NHIS survey is performed in approximately

20,000–30,000 U.S. participant homes annually (NCHS, 2021). This survey categorizes the health characteristics of the participants by demographic, socioeconomic, health access, and health behavior factors.

The outcome variable of interest was health equity, represented by the health status variable among adults with cardiometabolic conditions (hypertension, coronary heart disease, cholesterol, & diabetes). The independent variables were healthcare access (wellness visits and insurance status) and health behavior factors (alcohol use and physical activity). The covariates were sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI).

Literature Search Strategy

A literature review search covering the 5-year period from 2017 to 2022 was utilized to search within relevant peer-reviewed professional journals. The search engines used were Sage, Medline, PubMed, Science Direct, Google Scholar, and the Walden University Library via the EBSCO search engine. Federal government websites such as CDC, NHCS, AHA, and HRSA were also searched for relevant statistical and policy information. I reviewed earlier works for historical epistemology and account of the health equity concept and the conceptual framework of the ABM. The literature search used a combination of the following terms: *cardiovascular disease*, *cardiometabolic disease or disorders or conditions*, *heart disease*, *morbidity and mortality of cardiovascular disease*, *cardiometabolic disease and health equity*, *health equity and history of heath equity*, *National Health Interview Survey*, *diabetes*, *stroke*, *hypertension*, *coronary heart disease*, *high cholesterol*, *preventative wellness visits*, *life* *expectancy metrics*, *self-reported general health status*, *self-reported health outcomes*, *social determinants of health*, *Healthy People 2020, Healthy People 2030, health equity frameworks*, *health equity outcomes measurements*, and *Andersen behavioral model*. Topics that were unrelated were removed from the search collection, and if relevant terms and concepts were noted, the literature was reviewed further.

Literature Review Related to Key Concepts

Measuring health equity is an important step towards promoting fair opportunities for all people to live healthily and longer (Dover & Belon, 2019). Self-reported health status was selected as the variable to measure health equity outcome because researchers view it as a more detailed summary metric than life expectancy tables (Cho et al., 2022). The researchers Cho et al. (2022) further concluded that health status is an important prognostic factor for premature death. Numerous studies have demonstrated that self-reported health status indicators are important predictors of health outcomes (Deshpande et al., 2012).

Historically, insurance companies and other groups have relied on life expectancy tables for projections and death rate estimates; however, health status provides more in-depth health outcomes analysis than what insurance claims information can provide. Studies have shown that self-reported health status provides more information for population health equity and health outcomes (Cho et al., 2022; Tong et al., 2021). Wellness visits and health insurance are associated with increased socioeconomic status, and the trajectory of the health equity diagram by Davis et al. (2015) reflects the variables that represent positive health equity outcomes (Cho et al., 2022; Dyck et al., 2018; Singh

& Lee, 2021). Wellness visits are also beneficial because of their ability to reduce the risk of disease, disability, and death by improving determinants of health (Davis et al., 2015; Office of Disease Prevention and Health Promotion, n.d.). The United States has risen in life expectancy for 20 years, but disparities are still present between advantaged and disadvantaged groups, reflecting typical individuals with lower income and education.

Babitsch et al. (2012) researched studies that included predisposing factors such as age (15 studies), marital status (13 studies), sex (12 studies), education (11 studies), and race/ethnicity (10 studies). Enabling factors included income (10 studies), health insurance (nine studies), source of doctor care visits (nine studies), and need factors as self-reported health status (nine studies), evaluated health status (13 studies), and a variety of medical conditions, including CVD. The results indicated associations between the factors examined within the studies and the utilization of care. The population characteristics were found to have a strong influence on the direction of the covariate associations, so it was recommended that sociodemographic covariates be controlled and additional enabling and need variables be utilized in future studies (Babitsch et al., 2012). Research has shown that additional work is needed to decrease health inequity and increase health equity outcomes by targeting self-reported health status data in combination with healthcare access, health behaviors, and sociodemographic factors.

Definitions and Terms

The following are key definitions used in this study, as referenced by the CDC (n.d., 2022a):

Body mass index (BMI): The calculation of a person's weight in kilograms (or pounds) divided by the square of their height in meters (or feet). A high BMI indicates high body fatness.

Cardiometabolic conditions or *cardiometabolic disease*: Disease that affects the cardiovascular system and metabolic system individually or collectively, such as CHD, high cholesterol, hypertension, and diabetes.

Coronary heart disease (CHD) or *coronary artery disease (CAD)*: Caused by a buildup of plaque in the walls of the arteries decreasing the room for blood supply to the heart and other parts of the body.

Diabetes: Health condition that affects the body's ability to turn food into energy. The body either does not make enough insulin or cannot use it well. Type 1 diabetes is thought to be an autoimmune reaction that stops the body from making insulin. Type 2 diabetes is when the body does not use insulin well and cannot regulate blood sugar levels normally with a fasting plasma glucose level of greater than or equal to 126 mg/dL. There is no known method of preventing Type 1 diabetes, but Type 2 diabetes is preventable with healthy lifestyle changes.

Health equity: The state in which everyone has a fair and just opportunity to attain their highest level of health.

Heart attack or *myocardial infarction*: Occurs when part of the heart muscle does not get enough blood. The heart muscle is damaged the more time passes without treatment to restore blood flow.

Health status: The assessment of a person's well-being measured by perceived health rating (excellent, very good, good, fair, or poor). The reported health status is a predictor of mortality, morbidity, and functional status outcomes.

High cholesterol: Travels through the blood on proteins called *lipoproteins*; *plaque* is made up of cholesterol deposits. Elevated high cholesterol causes heart disease. There are two types of cholesterol:

- *Low-density lipoprotein (LDL) cholesterol*, sometimes called "bad" cholesterol, high levels of which increase risk for heart disease and stroke.
- *High-density lipoprotein (HDL) cholesterol*, sometimes called "good" cholesterol**.**

Hypertension or *high blood pressure*: Blood pressure higher than normal or consistently 130/80 mm/Hg or higher.

Physical activity: Vigorous activity that can make an individual feel better, function better, and sleep better. Physical activity improves overall health and reduces the risk of various chronic diseases. Adults ages 18–64 should have 150 minutes a week of moderate aerobic activity such as brisk walking and 2 days a week of activities that strengthen muscles.

Prevalence: The proportion of persons in a population who have a particular attribute or disease at a specific time, regardless of when they first developed the disease.

Stroke: Occurs when blood supply is blocked or a blood vessel in the brain bursts and parts of the brain become damaged or die.

Assumptions

My research was limited to a secondary dataset, and several assumptions were made. The primary assumption was that the NHIS survey instrument and process are valid and reliable. Another assumption was that the sample was representative of the U.S. population. It was assumed that survey respondents answered the questions truthfully and that their answers were accurately recorded.

Scope and Delimitation

This study targeted NHIS 2020 survey respondents who had cardiometabolic conditions and examined how healthcare access and health behaviors impact health equity outcomes while controlling for sociodemographic factors. Internal validity was upheld because the NHIS survey selection was completed by complex computer cluster sampling (NHCS, 2022). The scope and internal validity of my research were comprehensive.

The delimitation of my research was the target population composed of individuals who responded that they had hypertension, coronary heart disease, cholesterol, and/ or diabetes, although the NHIS captures other chronic health conditions such as several types of cancer, mental health, and injury-related conditions. The ultimate goal of my research was to advance health equity outcomes research for adults with cardiometabolic conditions.

Summary

Health equity outcomes research is a global and national priority, and health disparities were highlighted even more during the worldwide pandemic. Improving health equity outcomes is still a key goal from the CDC's Healthy People 2020 thru the Healthy People 2030 decade (CDC, n.d., 2022b). The significance of my research highlights the important fact that there is no consensus regarding what specific factors impact health equity outcomes the most. Government regulators and other researchers are requesting additional quantitative and qualitative research. My research addressed this issue and gap while capitalizing on the cross-sectional NHIS 2020 dataset.

This research may contribute to positive social change and benefit numerous stakeholders such as researchers, public health educators, public health communication specialists, and those in the pharmaceutical, device, and biologics industries. Additional stakeholders are the data registry owners, government legislature, government research institutions, medical research universities, private practice clinicians, patients with cardiometabolic issues, patient advocacy groups, regulatory and recruitment vendors, nonprofit organizations, consumer participant groups, and public health charitable foundations and organizations.

In summary, my work will be value-added by addressing this gap in the literature. One primary public health goal is to improve health equity, healthcare access, and positive health behaviors among communities to reduce the high disease morbidity and mortality rates in CVD prevalence. This research will advance the understanding of adults with one or more cardiometabolic conditions by addressing how behavioral, demographic, and cultural matters contribute to public health issues and disease burden (*Public Health Core Competencies*, 2021). This study can also influence the epidemiology core public health competency if the results are used to better understand heart disease and health equity outcomes within this targeted population (*Public Health Core Competencies*, 2021).

In Section 2, I will describe the methodology, research design, data collection, and data analysis plan.

Section 2: Research Design and Data Collection

Introduction

The purpose of this study was to examine how healthcare access (wellness visits and insurance status), health behaviors (alcohol use and physical activity), controlling for sociodemographic covariates (race/ethnicity, sex, age, education, marital status, family job status, and BMI), influence the health equity outcome health status in adults with cardiometabolic conditions from the 2020 NHIS dataset. This is a quantitative, cross-sectional secondary data doctoral study aimed at addressing health inequalities in this target population because the prevalence of morbidity and mortality remains critically important until mortality rates improve. I used binary logistic regression (BLR) to analyze the data for my research questions.

This section includes the research design of my study. This section includes my research design and rationale, methodology (highlighting the population and sampling procedures), dataset instrumentation, operationalization of variables, data analysis plan, threats to validity, and ethical considerations, ending with a section summary.

Research Design and Rationale

The NHIS is a cross-sectional household interview survey typically conducted in a face-to-face interview and with a participant self-reported response format within the residence of the participants (NCHS, 2021). Due to the global coronavirus pandemic and the mandatory U.S. lockdown stay order, the NHIS face-to-face interviews were conducted by phone primarily for the remainder of the year. The NHIS 2020 secondary dataset includes U.S.-based noninstitutionalized adults (18–85+ years old) within the 50 states and the District of Columbia (NCHS, 2021). Additional information will be provided about the NHIS dataset within the instrumentation section. The target population for this study was adults with hypertension, coronary heart disease, high cholesterol, and diabetes, known collectively as cardiometabolic conditions. The dependent or outcome variable was the health equity outcome represented by the health status variable among adults with cardiometabolic conditions (hypertension, coronary heart disease, cholesterol, & diabetes). The independent or predictor variables were healthcare access, represented by wellness visits, and insurance status variables and health behavior, represented by alcohol use and physical activity variables. The sociodemographic variables represented extraneous variables, but research and the conceptual model have shown that these variables are an important aspect of health equity outcomes. Research results depend on validity and ruling out other explanations such as control, extraneous, and/or confounding variables (Bhandari, 2022a). The covariates were sociodemographic factors that represent race/ethnicity, age, sex, marital status, education, family job status, and BMI variables.

The NHIS 2020 dataset is large (over 30,000 participants), public, readily available, and free. The NHIS 2020 survey background information, schematic information, interviewer training information, questionnaire, codebook, and technical information are also available for public access (NCHS, 2021). According to Wang and Cheng (2020), a cross-sectional study is a type of observational study that is often used to measure the prevalence of health outcomes in an easy and inexpensive way. The authors also indicated that cross-sectional studies are usually chosen from the available population of potential relevance to the study question or topic. The exposure and outcome variables simultaneously limit the ability to determine cause-and-effect relationships and may provide prevalence information about outcomes that could influence and inform future studies (Wang & Cheng, 2020). There are many advantages to conducting a cross-sectional study design to provide descriptive and analytic information that advances the knowledge of health equity relating to cardiometabolic conditions.

The primary purpose of the NHIS is to monitor the health of the U.S. population. It is used to track illnesses, disabilities, health behaviors, accessibility, health insurance coverage, and progress towards reaching national health objectives (NCHS, 2021). These surveillance data have been collected annually since 1957 by the NCHS branch of the CDC, and the U.S. Census Bureau trains the interviewers using modern computer-assisted questionnaires (NCHS, 2021). During the face-to-face interview, the self-reported responses are entered into the computer, and subsequent survey questions are populated based on previous answers, which are all automatically saved in real time (CDC, 2018). The NHIS dataset is representative of the population consisting of approximately 35,000 potential survey participants annually.

Methodology

Population

The target population for this study included 31,568 noninstitutionalized adult (age 18 +) NHIS 2020 survey participants with self-reported "yes" responses to cardiometabolic conditions (hypertension, high cholesterol, coronary heart disease, and diabetes). The target population of survey participants with cardiometabolic conditions was as follows: 11,494 stated “yes” to hypertension, 9,865 stated “yes” to high cholesterol, 1,901 stated “yes” to coronary heart disease, and 3,356 stated “yes” to diabetes, for a total of 26,616. This total accounts for an individual selecting “yes” to one or multiple conditions. The sampling procedures document the targeted sample group of 15,955 participants with cardiometabolic conditions, which accounts for each individual regardless of if they selected one or more of the specified conditions. The Sample Adult (SA) participant responds to the interview survey questions unless they are physically or mentally unable to do so, in which case a knowledgeable proxy answers for the SA (NCHS, 2021). The NHIS sample was based on the estimates that approximately 58,800 addresses were pulled to yield roughly 35,000 households each year. There were 409 proxies that answered the 2020 NHIS for the SA.

Sampling and Sampling Procedures

The NHIS uses geographically clustered sampling techniques to systematically select the sample of dwelling units starting with 1,689 large geographic areas and approximately 5,350–5,650 home addresses monthly from cluster groups all over the United States (NCHS, 2021). This type of complex single-stage probability sampling design is often used with very large datasets to help with costs and time restrictions associated with collecting data on thousands of participants from across the country (Kneipp & Yarandi, 2002). The authors also noted that research and current literature support applying sample and variance estimation weights to data derived from complex sampling of large datasets. The current cluster sampling plan for NHIS has been determined for the 2016–2025 years based on results from the 2010 U.S. decennial census (Moriarity et al., 2022). The NHIS datasets are reliable and openly accessible to the public, and the NCHS provides numerous documents with each dataset free of charge. The weighting procedures and bias assessment document for the 2020 NHIS states that this sample dataset was largely unbiased and specifically that no bias was detected for health status, health insurance coverage, or health behaviors (Bramlett et al., 2021). The weighting used multilevel logistic regression models to predict response probabilities and ranking procedures to include variables for calibration to population control totals (Mercer et al., 2018; NCHS, 2021). The other documents available were the interviewer questionnaires (English and Spanish), field interviewer manual, codebook, summary documents, flowcharts, and actual dataset files provided in SPSS, SAS, STATA, and CSV formats (NCHS, 2021).

The 2020 NHIS dataset has relevant health information for the research target sample of adults with cardiometabolic conditions. The sampling procedures indicate that survey participants received an advanced letter about the NHIS indicating that they had been selected to participate, with a follow-up phone call to schedule the interview. The participants were assured that all identifying information collected by NHIS would be held confidential and would not be disclosed or released to anyone without the written consent of the participant (NCHS, 2021). Once the interview started, the interviewer first asked specified eligibility questions to determine if the participants met the NHIS standard inclusion criterion. The codebook confirms that for the NHIS 2020, there were 31,568 adults interviewed, and for the cardiometabolic conditions targeted, 11,494 answered “yes” to hypertension, 9,865 had high cholesterol, 1,901 had coronary heart disease, and 3,356 had diabetes, for a total of 26,616 or 84.3% occurrence in the sample. The focus was not on occurrences (an individual could have one or all four conditions), but on the count of participants who selected at least one condition. The select cases option in SPSS separated participants with at least one cardiometabolic condition from the dataset to yield the targeted sample population of 15,955.

G* Power analysis version 3.1.9.7 was used to calculate the appropriate sample size for this study. The research questions’ dependent variables, independent variables, and covariates will be presented in detail in the data analysis section. A summary overview will document the power analysis for each research question. In my research analysis, I will use BLR. The dichotomous dependent outcome variable was health status (excellent/very good or other). The primary predictor variable selected for the power analysis for healthcare access was the wellness visit variable, and the physical activity variable was for the health behavior predictor variable.

The power analysis in Research Question 1 (RQ1) and Research Question 2 (RQ2) regarding the main predictor variables wellness visits and physical activity based on the current literature estimated approximately 50% probability that both main predictor variables would result in an excellent/very good general health status response (Borsky et al., 2018; Posadzki et al., 2021; Tong et al., 2021; Whitfield et al., 2021). Logistic nonparametric regression analysis is utilized when numerical variables are not normally distributed and the outcome variable is binary (Faul et al., 2009). The input parameters are priori analysis, *Z* tests, two-tailed, logistic regression, and options probabilities. The probability of intent of excellent/very good health status response given that participants had wellness visits and appropriate physical activity is 50% (0.50) and is represented by Pr(Y = 1|X = 1) H_1. The probability of intent of excellent/very good health status response when participants did not have wellness visits or appropriate physical activity is 30% (0.30) and is represented by Pr(Y = 1|X = 0) H_0. The odds ratio was calculated using Cohen's *d* effect size converter of medium effect (0.50), yielding an odds ratio of 2.477 (Lin, n.d.). The statistical significance level is set at alpha (α) = 0.05, which provides the effect size and strength of the association between the dependent, independent, and covariates or confounding variables in this study. The power (1- β) was set at 80%, which is the probability of estimated participants with assumptions sufficient to find a statistical effect size. The R^2 value is .25, the distribution is binomial, and the x parm π is 0.50. After calculation, the total sample size for both RQ1 and RQ2 is 220 participants. Figure 3 depicts the sample size calculation.

The power analysis for Research Question 3 (RQ3) uses the continuous variable age as the continuous main covariate variable. The input parameters are priori analysis, *Z* tests, two-tailed, logistic regression, and options odds ratio is selected. The odds ratio was set at 3 for medium effect. The probability of intent of excellent/very good health status response when participants' age predictor is at one standard deviation above the mean of 53.61 is 30% (0.30) and is represented by Pr(Y = 1) H_0. The statistical significance level is set at alpha (α) = 0.05, which provides the effect size and strength of the association between the dependent variables, independent variables, and covariates or confounding variables in this study. The power (1- β) was set at 80%, which is the probability of estimated participants with assumptions sufficient to find a statistical effect size. The R^2 value is .23, the distribution is normal, the x parm μ is 0, and the x parm π is 1. After calculation, the total sample size for RQ3 was 59 participants. Figure 4 depicts the sample size calculation.

Figure 3

G Power Analysis for Research Questions 1 and 2*

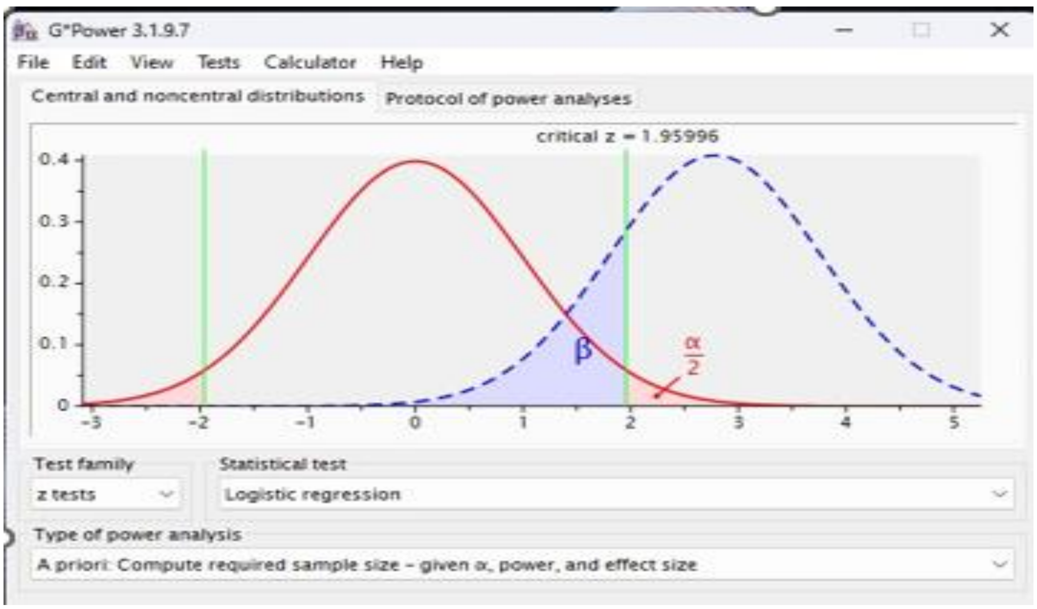
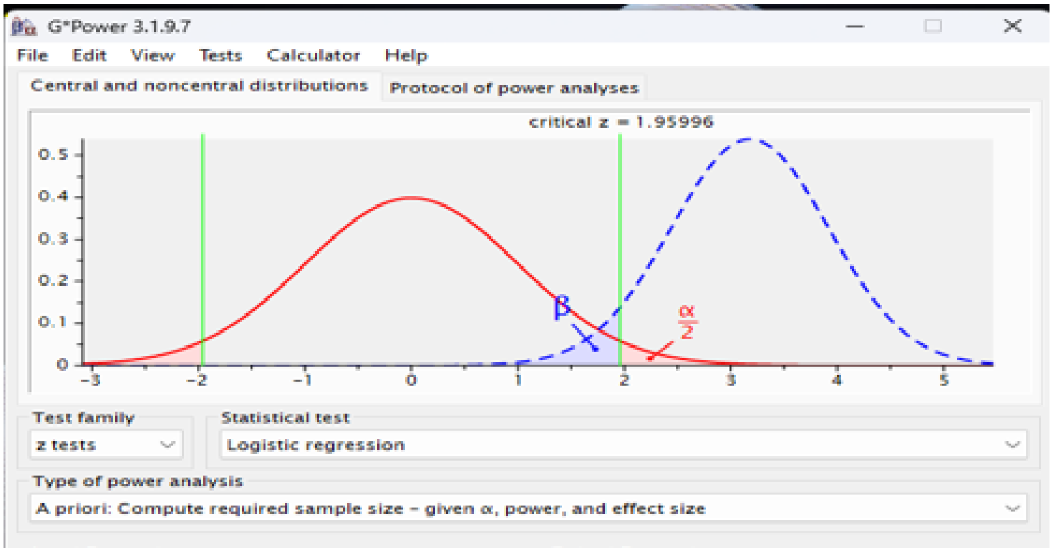


Figure 4

G Power Analysis for Research Question 3*



Instrumentation and Operationalization of Constructs

The U.S. Department of Health and Human Services is the lead agency that has captured the NHIS health surveillance data annually since 1957 through the NCHS branch of the CDC, and the U.S. Census Bureau trains the interviewers using modern computer-assisted questionnaires (NCHS, 2021). The NHIS is a quantitative cross-sectional household interview survey performed annually to monitor the health of the U.S. population residing within the 50 states and territories. Utilizing this dataset was appropriate to the current study because the NHIS is used to follow the prevalence and incidences of illnesses and disabilities and document progress toward reaching national health objectives (NCHS, 2021). The NHIS 2020 survey dataset was published and available for public use in 2021, and it is the gold standard in capturing health related population-based data.

The published reliability and validity of the NHIS 2020 are detailed in the 2020 NHIS Survey Description document (NHCS, 2021). U.S. Census Bureau interviewers are trained for consistency, and they help eliminate interviewer bias. Supervisors accompany the interviewers, and their work is monitored by the PANDA system that analyzes performance regarding response rates, completion rates, item response times, and other data quality indicators. A valid computer-assisted personal interviewing (CAPI) system is used during the participant interview with built-in hard and soft edit checks in real time. The Blaise computer software guides the interviewer through the questionnaire and allows data entry for survey responses directly into the computer. To help prevent data entry errors and range inconsistencies, out of range value checks are automatically flagged and must be addressed prior to moving forward. This type of “hard edit” would flag for an age of 350 versus 35 years old, for example. The “soft edits” are automatically flagged, but the interview may continue with or without a correction, such as an extreme height but within an acceptable range. Finally, values that are not in range but appropriate are verified as missing or not ascertained if the skip patterns are appropriate (NHCS, 2021).

Study Variables

Table 1 through Table 4 show the research questions, dependent variables, independent variables, covariates, and dummy recodes at the conclusion of the data analysis section. In this section, I describe the operation for each variable, the level of measurement, the variable code, and the dummy variable recode/renaming of the variable for the BLR analysis. All variables that list “refused,” “not ascertained,” and “don’t know" were excluded from the analysis. All cases with missing values were also excluded.

Dependent Variable

The dependent variable is health status. The NHIS asks: Would you say your health in general is excellent, very good, good, fair, or poor? This categorical variable is ordinal, but I will use a common approach referred to as the median split to the sample around the median to create a binary variable. According to MacCallum et al. (2002), the median split approach is used with both continuous and ordinal variables by placing all cases that are below and above the split into two groups. Health status is measured most often on an ordinal scale but, studies conclude that using a dichotomized outcome measure has only slightly less power than ordinal regression (Armstrong & Sloan, 1989). Recent analysis concluded that median splits with continuous versus ordinal variables have historically more criticism, but the study indicates median splits for ordinal variables are valid and acceptable, if, the independent variables are uncorrelated (Iacobucci et a., 2015). The new variable represents excellent/ very good and other, determined by an approximate median of 57.65 % versus 42.29%, respectively, for the new binary health status.

Independent Variables

The wellness visits and health insurance status variables represent the independent variables that measure healthcare access. The NHIS asks: Was last visit a wellness visit? This categorical variable is nominal (yes, no, refused, not ascertained, & don't know), and this variable will remain the same. For the second variable, the NHIS asks: Do you have health insurance? This categorical variable is nominal (yes, no, refused, not ascertained, & don't know), and this variable will remain the same.

The alcohol drinking status and physical activity variables represent the independent variables that measure health behaviors. The NHIS asks: What is your alcohol drinking status? This categorical variable is nominal (lifetime abstainer, former infrequent, former regular, former unknown frequency, current infrequent, current light, current moderate, current heavier, current drinker frequency unknown, & drinking status unknown), and this variable will remain the same. For the second variable, the NHIS asks: Have you met the physical activity guidelines for aerobic and/or strengthening activity? This categorical variable is nominal (meets neither criteria, meets strength only, meets aerobic only, meets both criteria, & not ascertained), and this variable will remain the same.

Covariate Sociodemographic Variables

The sociodemographic covariate variables are represented by race/ethnicity, age, sex, marital status, education, family job status, and BMI variables. The covariates NHIS question asks: What is your race/ethnicity (Hispanic, Non-Hispanic (NH) White only, NH Black/ African American only, NH Asian only, NH AIAN only, NH AIAN and any other group, refused, not ascertained, and don't know)? This variable is a nominal categorical variable that will remain the same. The next NHIS question: What is the age of the sample adult (SA) (18-84, 85+, refused, not ascertained, and don't know)? This is a continuous variable that ranges from 18- 84+ years old. This variable will stay continuous, and a new variable will be created ordered after the U.S. census age categories (18-20; 21-44; 45-64, and 65+) (US Census Bureau, 2023). When continuous data such as age is reduced to ordered categories, it provides advantages in data analysis because it allows the researcher to review interactive relationships between the categories (Greenacre, 2016; Nishisato, 2007). The next NHIS question asks: What is your sex (male, female, refused, not ascertained, and don't know)? This variable will remain dichotomous male and female. The next NHIS question asks: What is the SA's marital status (married, living with partner together as an unmarried couple, neither, refused, not ascertained, and don't know)? The variable code for this nominal variable will remain the same. The next NHIS question asks: What is the highest level of education of all the adults in the SA's family (never attended/kindergarten only, grade 1-11, 12th grade & no diploma, GED or equivalent, high school graduate, some college/ no degree, associates degree, bachelor's degree, master's degree, professional school degree {MD, DDS, DVM, JD}, doctoral degree {PhD, EdD}, refused, not ascertained, and don't know)? This nominal variable will remain the same. The next NHIS question asks: How many adults in the SA's family work full-time (0 adults, 1 adult, 2 adults, 3+ adults, and not ascertained)? This nominal variable will remain the same. The next NHIS question asks: What is your body mass index (BMI) (underweight, healthy weight, overweight, obese, and unknown)? The nominal variable will remain the same.

Data Analysis Plan

The Statistical Package for the Social Sciences (SPSS) Version 28 was used for the statistical analysis of the data. BLR will explore the impact on the four independent variables on the dependent dichotomous variable holding constant the confounding covariates. All three research questions will provide descriptive and inferential statistical analysis. The results section will detail descriptive statistics of each variable such as the level of measurement, central tendency, and variation will be described. Detailed analysis and hypotheses results will also be reported.

The dependent variable (DV) was recoded as a binary variable and the age covariate created for the census age bands was recoded to a four-category ordinal variable. A Chi-square test will analyze the association between variables, and Cramer's V will measure the effect size of the association, and the p value significance is less than 0.05 (Walden University, 2021). When BLR is used the DV outcome must be binary, but the IV's can be either categorical and/ or continuous (Walden University, 2019). All of the ordinal predictor variables will be treated as nominal variables during the analysis. The BLR model is not linear and does not use R2, similar to linear regression, instead it uses a mathematical transformation term called "logits" (Crowson, 2019). The BLR has an "S" curve or logistic curve instead of the standard linear curve thus instead of predicting the probability for intercepts and slopes it uses predicted logit, which is similar to probability (Crowson, 2019). The BLR model assumptions are flexible such as observations should be independent, no multicollinearity among the IV's, no extreme outliers, and the sample size should be over 50 observations, according to Latif (2021).

Table 1

Research Question 1: To What Extent Is Healthcare Access (Wellness Visits and Insurance Status) a Predictor of the Health Equity Outcome as Measured by Health Status in Adults With Cardiometabolic Conditions in the United States, While Controlling for Sociodemographic Factors (Race/Ethnicity, Age, Sex, Marital Status, Education, Family Job Status, and BMI)?

Research variable	Variable code	Unit of measurement	Recoded variable	New variable
Dependent variable (DV)				
DV—Health status	PHSTAT_A	Ordinal	Yes	NEWPHSTAT
Independent variable (IV)				
IV—Wellness visits	WELLNESS_A	Nominal	No	
IV—Health insurance status	HICOV_A	Nominal	No	
Covariates:				
Race/ethnicity	HISPALLP_A	Nominal	No	
Age	AGEP_A	Nominal	Yes	CENSUSAGE
Sex	SEX_A	Nominal	No	
Marital status	MARITAL_A	Nominal	No	
Education	MAXEDUC_A	Nominal	No	
Family FT job status	PCNTADTWFP_A	Nominal	No	
BMI	BMICAT_A	Nominal	No	

Table 2

Research Question 2: To What Extent Are Health Behavior Factors (Alcohol Use and Physical Activity) a Predictor of the Health Equity Outcome as Measured by Health Status in Adults With Cardiometabolic Conditions in the United States, While Controlling for Sociodemographic Factors (Race/Ethnicity, Age, Sex, Marital Status, Education, Family Job Status, and BMI)?

Research variable	Variable code	Unit of measurement	Recoded variable	New variable
Dependent variable (DV)				
DV—Health status	PHSTAT_A	Ordinal	Yes	NEWPHSTAT
Independent variable (IV)				
IV—Alcohol status	DRKSTAT_A	Nominal	Yes	NEWALCOHOL
IV—Physical activity	PA18_05R_A	Nominal	No	
Covariates:				
Race/ethnicity	HISPALLP_A	Nominal	Yes	NEWRACE
Age	AGEP_A	Nominal	Yes	CENSUSAGE
Sex	SEX_A	Nominal	No	
Marital status	MARITAL_A	Nominal	No	
Education	MAXEDUC_A	Nominal	Yes	NEWEDU
Family FT job status	PCNTADTWFP_A	Nominal	No	
BMI	BMICAT_A	Nominal	No	

Table 3

Research Question 3: To What Extent Are Sociodemographic Factors (Race/Ethnicity, Age, Sex, Marital Status, Education, Family Job Status, and BMI) a Predictor of the Health Equity Outcome as Measured by Health Status in Adults With Cardiometabolic Conditions in the United States?

Research variable	Variable code	Unit of measurement	Recoded variable	New variable
Dependent Variable (DV)				
DV—Health status	PHSTAT_A	Ordinal	Yes	NEWPHSTAT
Covariates:				
Race/ethnicity	HISPALLP_A	Nominal	Yes	NEWRACE
Age	AGEP_A	Nominal	Yes	CENSUSAGE
Sex	SEX_A	Nominal	No	
Marital status	MARITAL_A	Nominal	No	
Education	MAXEDUC_A	Nominal	Yes	NEWEDU
Family FT job status	PCNTADTWFP_A	Nominal	No	
BMI	BMICAT_A	Nominal	No	

Table 4

Dependent and Covariate Dummy Code Reference

Research variable	Variable code	New variable	REFERENCE=0	REFERENCE = 1 (TARGET)
Dependent variable (DV)				
DV—Health status	PHSTAT_A	NEWPHSTAT	Other	Excellent/very good
Covariates:				
Age	AGEP_A	CENSUSAGE	18–20	21–44 45–64 65+

Threats to Validity

External Validity

Research that draws incorrect data analysis inferences is a direct threat to external validity, such as using incorrect sampling procedures such as oversampling or incorrect sampling (Frankfort-Nachmias & Nachmias, 2008). One common external validity threat is population validity which involves reasonably generalizing findings from your sample to a larger group of people or the population at large (Bhandari, 2022a). The results from this study will only relate to noninstitutionalized adults in the United States, and the COVID-19 pandemic impacted the way in which the surveys were administered, from face-to-face to telephone interviews. There are also errors and other issues associated with research. A P-value < 0.05 indicates the statistical significance and rejection of the null hypothesis. Type I sampling error detects a false positive and rejects the null hypothesis when it is true, or an association is detected that is not present (Bhandari, 2022b). An example is when a person takes a flu test, and the results show the flu test as positive, but you do not actually have the flu (false positive). The author also states type II sampling error is a false negative result or a failure to identify a positive relationship. An example is when the person is test shows negative for the flu, and that person does have the flu (false negative).

Internal Validity Threats

Internal validity threats are important because countering them will help establish trustworthy research (Bhandari, 2022a). This should be considered during the design phase of the study. Historical bias is an issue that indicates important historical events, such as the global pandemic, and this may impact survey participants thoughts. The NHIS 2020 dataset could have some internal and external validity threats because all participants responses are self-reported. The NHIS survey attempted to control validity threats by ensuring the interviewers are adequately trained in a consistent way.

Ethical Procedures

This study will use NHIS 2020 de-identified secondary data available for public use. No ethical issues were identified in this study, and none of the participants information will be released. Also, the geographic state identifiers and other geographic variables are also masked for added data privacy protection (NCHS, 2021). Institutional review board (IRB) approval will be obtained prior to data analysis to ensure participant privacy is protected.

Summary

According to Turner et al. (2022), as data-driven evidence-based medicine increases in importance, researchers must be able to improve health equity outcomes-based research for future public health programming and analysis. In this chapter, I presented the study methodology, sampling information, research design, independent and dependent variables, data collection information, data analysis plan, ethical considerations, and threats to internal and external validity. This study aims to analyze cardiometabolic illnesses collectively to increase understanding and provide multiple stakeholders with information to promote health equity. Chapter 3 will provide the results of the study.

Section 3: Presentation of the Results and Findings

Introduction

The aim of this quantitative, cross-sectional research using the NHIS 2020 secondary dataset was to analyze how the predictor variables of healthcare access and health behaviors influence health equity outcomes (health status) while controlling for sociodemographic factors among adults with hypertension, high cholesterol, coronary heart disease, and diabetes (cardiometabolic conditions). The sociodemographic factors were used to analyze health equity outcomes (health status) with the variables of interest. The wellness visits and insurance status represent healthcare access predictor variables used to for RQ1, and the alcohol use and physical activity predictor variables represent health behaviors for RQ2. Race/ethnicity, sex, age, education, marital status, family job status, and BMI represent covariates for the sociodemographic variables in RQ3. Binary logistic regression was used to analyze all three research questions against the outcome variable of health status represented by *excellent/very good* and *other*.

The research questions and hypotheses that guided this study were the following:

Research Question 1: To what extent is healthcare access (wellness visits and insurance status) a predictor of the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI)?

H_{01}: Healthcare access (wellness visits and insurance status) does not predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI).

H_{A1}: Healthcare access (wellness visits and insurance status) does predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI).

Research Question 2: To what extent are health behavior factors (alcohol use and physical activity) a predictor of the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI)?

H_{02}: Health behavior factors (alcohol use and physical activity) do not predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI).

H_{A2}: Health behavior factors (drug use, tobacco use, physical activity, and immunization) do predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI).

Research Question 3: To what extent are sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI) a predictor of the health equity outcome health status in adults with cardiometabolic conditions in the United States?

H_{03}: Sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI) do not predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States.

H_{A3}: Sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI) do predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States.

In this chapter, I will cover the presentation of the results and findings of the study, divided into three subsections. The data collection will be discussed in the initial section, followed by the baseline demographic characteristics and descriptive statistics information about the secondary dataset sample. Assumptions will be evaluated, followed by the findings organized by research questions and hypotheses in the third section. The section will conclude with a summary. In the final chapter, I then describe how this research is applicable to professional practice and positive social change.

Data Collection and Secondary Dataset

Timeframe for Data Collection

The NHIS 2020 secondary dataset was collected during the entire year of 2020 and made publicly available in 2021. The 2020 sample adult file was downloaded from the NHIS site and then uploaded to SPSS version 28. A frequency analysis compared the variables of interest against the 2020 NHIS codebook, and there were no discrepancies noted.

Discrepancies of the Secondary Dataset

There were no data collection issues or discrepancies identified. There were three variable modifications that were updated after Section 2. The independent variable for alcohol use was transformed to former and current alcohol use. The covariate for ethnicity/race was transformed to combine other and mixed races into one category. The next covariate for education was transformed to high school and below, some college, associate's degree, bachelor's degree, and master's degree and above. The age covariate was transformed from a continuous variable to categories to reflect the U.S. Census age groups described in Section 2. Please see Table 5 for the final modifications of variables for this analysis.

Table 5

Dependent, Independent, and Covariate Dummy Code Reference

Research variable	Variable code	New variable	REFERENCE = 0	REFERENCE = 1 (TARGET)
Dependent variable (DV)				
Health status	PHSTAT_A	NEWPHSTAT	Other	Excellent/very good
Independent variable (IV)				
Alcohol status	DRKSTAT_A	NEWALCOHOL	Former drinker	Current infrequent Current light Current moderate Current heavy
Covariates:				
Race/ethnicity	HISPALLP_A	NEWRACE	White	African American Hispanic Asian American Indian/ Alaskan Native Other/Mixed
Age	AGEP_A	CENSUSAGE	18–20	24–44 45–64 65+
Education	MAXEDUC_A	NEWEDU	High school & below	Some college Associate's degree Bachelor's degree Master's & above

Analyzing the Secondary Dataset

Dataset and Demographic Characteristics

In 2020, the NHIS surveyed 31,568 noninstitutionalized adults (age 18 +) in the United States; participants who self-reported "yes" responses to at least one or more cardiometabolic conditions (hypertension, high cholesterol, coronary heart disease, and diabetes) made up the target population for my research. The targeted survey participants with cardiometabolic conditions were as follows: 11,494 or 36.41% stated “yes” to hypertension, 9,865 or 31.25% stated “yes” to high cholesterol, 1,901 or 6.02% stated “yes” to coronary heart disease, and 3,356 or 10.63% stated “yes” to diabetes. This yields a total cardiometabolic conditions targeted sample group of 15,955 or 50.54%, in which one or more of the specified conditions were confirmed. Please see Table 6.

Table 6

Target Cardiometabolic Condition Sample Size

Cardiometabolic conditions	Responded “yes”
Hypertension	11,494
High cholesterol	9,865
Coronary heart disease	1,901
Diabetes	3,356

Baseline descriptive data are captured in Table 7 and Table 8 below, but an overview is provided for context. The following are demographic and variable descriptive data. Data on sex for this sample reflect that among survey participants, 47.3% were men and 52.7% were women. There were 72.6% non-Hispanic (NH) Whites, 11.5% NH Black/African Americans, 9.6% Hispanics, 4.0% NH Asians, .06% NH American Indian/ Alaskans, and 1.6% other and mixed races. Age data followed the standard U.S. Census age groupings; .20% of this target sample were 18 to 20 years old, 13.4% were 21 to 44 years old, 36.7% were 45 to 64 years old, and 49.7% were age 65 and older. Among participants, 46.7% were married, 4.1% were cohabitating, and 46.3% were not married or cohabitating. There were 27.2% of participants who had obtained a high school diploma and below, 15.3% who had achieved some college but no degree, 15.0% who had received an associate's degree, 23.0% who had received a bachelor's degree, and 19.2% who had received a master's degree or higher. Data on the number of adults working in the family full time indicated that 55.2% of participants had zero adults working full time, 29.1% of participants had one family member who worked full time, 13.7% had two family members working full time, and only 1.8% had three or more adults working full time in the family. The final sociodemographic variable was BMI. Only 1.0% of survey participants were underweight, 23.0% were a healthy weight, 34.6% were overweight, and 39.0% were obese. The summary sociodemographic data revealed that this targeted sample of participants, adults with cardiometabolic conditions (hypertension, high cholesterol, coronary heart disease, and diabetes), was predominantly White; slightly above half were women; most were college educated; most were middle aged and above; most were overweight or obese; half were married; and a little over half had no family members in the home working full time.

The independent variables wellness visits and insurance status (healthcare access) and alcohol use and physical activity (health behavior) descriptive statistics will also be summarized. There were 81.3% of participants who answered that their last visit was a wellness visit, and 96.1% of participants answered that they had health insurance. The new alcohol use variable indicated that 34.5% of participants were former drinkers, 14.1% were current infrequent drinkers, 26.0% were current light drinkers, 15.9% were current moderate drinkers, and 6.1% were current heavy drinkers. There were 51.2% of participants who did not meet the criteria of physical activity, 6.5% who met the strength only physical activity criteria, 22.9% who met the aerobic only physical activity criteria, and 15.7% who met both strength and aerobic activity criteria. In summary, for the healthcare access variables, the majority of participants had health insurance and wellness visits. The health behaviors summary data showed that approximately 62% were current alcohol drinkers, and physical activity data showed that approximately half did and half did not have physical activity.

Table 7

Variable Participant Response Versus Missing

Total target sample size	15,955	Response	Missing
Dependent variable			
Health status		15,955	0
Independent variables			
Wellness visits		15,850	105
Insurance status		15,944	11
Alcohol status		15,399	556
Physical activity		15,378	577
Covariates			
Race/ethnicity		15,955	0
Age		15,955	0
Sex		15,954	1
Marital status		15,491	464
Education		15,921	34
Family job status—FT		15,915	40
BMI		15,569	386

Table 8

Variable Descriptive Statistics

Total target sample size	Category	*N*	%
Dependent variable			
Health status		15,955	100.0
	Excellent/very good	6,818	42.7
	Other health status	9,137	57.3
Independent variables			
Wellness visits (WV)		15,850	99.3
	WV—Yes	12,978	81.3
	WV—No	2,872	18.0
Insurance status		15,944	99.9
	Insurance—Yes	15,337	96.1
	Insurance—No	607	3.8
Alcohol drinker (AD)		15,399	96.5
	Former AD	5,497	34.5
	Current infrequent AD	2,253	14.1
	Current light AD	4,141	26.0
	Current moderate AD	2,533	15.9
	Current heavy AD	975	6.1
Physical activity (PA)		15,378	96.4
	No PA	8,165	51.2
	Strength only PA	1,044	6.5
	Aerobic only PA	3,661	22.9
	Both PA	2,508	15.7
Covariates			
Race/ethnicity		15,955	100.0
	Non-Hispanic (NH) White	11,586	72.6
	NH Black/African American	1,840	11.5
	Hispanic	1,537	9.6
	NH Asian	634	4.0
	NH American Indian/Alaskan	103	.60
	Other/Mixed race	255	1.6
Age		15,399	100.0
	18–20 years	39	.20
	21–44 years	2,133	13.4
	45–64 years	5,861	36.7
	65+ years	7,922	49.7
Sex		15,954	100.0
	Male	7,551	47.3

Total target sample size	Category	*N*	%
	Female	8,403	52.7
Marital status		15,491	97.1
	Married	7,446	46.7
	Cohabitating	656	4.1
	Neither	7,389	46.3
Education		15,921	99.8
	High school & below	4,344	27.2
	Some college	2,443	15.3
	Associate's degree	2,399	15.0
	Bachelor's degree	3,673	23.0
	Master's degree & above	3,062	19.2
Family job status—FT		15,915	99.7
	0 adults working FT	8,806	55.2
	1 adult working FT	4,637	29.1
	2 adults working FT	2,188	13.7
	3+ adults working FT	284	1.8
BMI		15,569	97.6
	Underweight	157	1.0
	Healthy weight	3,664	23.0
	Overweight	5,522	34.6
	Obese	6,226	39.0

Representative Sample

The NHIS attempts to obtain a representative sample of the U.S. total population by using a complex, multistage probability sample that incorporates stratification, clustering, and weighting. The NHIS 2020 is a household, face-to-face, or during the COVID-19 pandemic, a telephone-based interviewer/participant survey that captures the participant responses for this annual health survey of approximately 36,000 people in 35,000 households annually.

Results

Binary Logistic Regression Assumptions

Binary logistic regression was used to analyze how four independent variables influenced the binary health status (excellent/very good or other) while controlling for the seven sociodemographic variables. According to Laerd Statistics (2017), there are seven assumptions that must be met to run a binary logistic regression analysis. Assumption 1 is that one must have one dichotomous dependent, and this was satisfied by my health status variable (excellent/very good or other). Assumption 2 is that one must have one or more independent variables that are measured on a continuous or nominal scale, and I had 11 independent variables that were all treated as nominal for this analysis. Assumption 3 is that one must have independence of observations between the binary dependent variable and all of the nominal predictor variables, and this assumption is not something a researcher can test for using SPSS; this is a study design issue if noted. They must be mutually exclusive and exhaustive, and my outcome and predictor variables met this assumption. Assumption 4 is that it is important to have 15 cases per independent variable, and my sample size was significantly more than the 165-case sample size requirement for this assumption. Assumption 5 is that there needs to be a linear relationship between a continuous independent variable and the logit transformation of the binary dependent variable, and I had no continuous independent variables. Assumption 6 is that the data must not show multicollinearity (two or more independent variables are highly correlated with each other), and my correlation coefficients were less than .70. Tolerance/VIF values indicated no multicollinearity among my independent variables. All Tolerance values were greater than .10, and all VIF values were less than 10 (Walden University, 2019). Assumption 7 is that there should be no significant outliers, and there were no significant outliers identified (Laerd Statistics, 2017). The BLR assumptions were all met for this test analysis.

The chi-square test was performed to analyze the associations of all the 12 nominal variables: the binary health status variable, wellness visits, health insurance, alcohol use, physical activity, race/ethnicity, age, sex, marital status, education, family job status, and BMI. The analysis showed that all of the variables were statistically significant. The Cramer's V results and the *df* were examined to determine the effect size: wellness visits = 0.07, health insurance = 0.04, alcohol use = 0.21, physical activity = 0.27, race/ethnicity = 0.14, age = .067, sex = .026, marital status = 0.10, education = 0.24, family job status = 0.14, and BMI = 0.17 respectively. The statistical significance and confidence intervals were reported at 5% and 95%, respectively. Please see Table 9 below.

Table 9

Master Crosstab—All Variables

All nominal variables	Chi-square, *df* & Cramer's V—Effect size
Health status v/s wellness visits	χ^2 (1) = 78.38, p < .001—Small effect
Health status v/s insurance status	χ^2 (1) = 27.26, p < .001—Small effect
Health status v/s alcohol use	χ^2 (4) = 666.87, p < .001—Medium effect
Health status v/s physical activity	χ^2 (3) = 1135.43, p < .001—Large effect
Health status v/s race/ethnicity	χ^2 (5) = 315.04, p < .001—Medium effect
Health status v/s age	χ^2 (3) = 72.05, p < .001—Small effect
Health status v/s sex	χ^2 (1) = 10.70, p < .001—Small effect
Health status v/s marital status	χ^2 (2) = 168.94, p < .001—Small effect
Health status v/s education	χ^2 (4) = 900.34, p < .001—Medium effect
Health status v/s family job status	χ^2 (3) = 299.72, p < .001—Small effect
Health status v/s BMI	χ^2 (3) = 461.36, p < .001—Medium effect

Analysis for Research Question 1 and Research Question 2

Binary logistic regression was used to analyze how four predictor variables (wellness visits, health insurance status, alcohol use, and physical activity) influenced the binary health status (Excellent/Very Good or Other) while controlling for the seven sociodemographic variables (race/ethnicity, age, sex, marital status, education, family job status, and BMI). Tables 10 and 11 show the BLR results and the summary is provided after RQ1 and RQ2.

The variable participant response selection was determined to be in either reference or target grouping for each of the 12 total categorical nominal variables for the BLR analysis. Please see Table 10.

Table 10

Variable Grouping (Reference v/s Target)

Total target sample size	Category	Reference v/s target group	%
Dependent variable			
Health status			**100.0**
	Excellent/very good		42.7
	Other health status	***Reference***	57.3
Independent variables			
Wellness visits (WV)			**99.3**
	WV—Yes		81.3
	WV—No	***Reference***	18.0
Insurance status			**99.9**
	Insurance—Yes		96.1
	Insurance—No	***Reference***	3.8
Alcohol drinker (AD)			**96.5**
	Former AD	***Reference***	34.5
	Current infrequent AD		14.1
	Current light AD		26.0
	Current moderate AD		15.9
	Current heavy AD		6.1
Physical activity (PA)			**96.4**
	No PA	***Reference***	51.2
	Strength only PA		6.5
	Aerobic only PA		22.9
	Both PA		15.7
Covariates			
Race/ethnicity			**100.0**
	Non-Hispanic (NH) White	***Reference***	72.6
	NH Black/African American	1840	11.5
	Hispanic	1537	9.6
	NH Asian	634	4.0
	NH American	103	.60
	Indian/Alaskan	255	1.6

Total target sample size	Category	Reference v/s target group	%
	Other/mixed race		
Age			**100.0**
	18–20 years	***Reference***	.20
	21–44 years		13.4
	45–64 years		36.7
	65+ years		49.7
Sex			**100.0**
	Male	***Reference***	47.3
	Female		52.7
Marital status			**97.1**
	Married		46.7
	Cohabitating		4.1
	Neither	***Reference***	46.3
Education			**99.8**
	High school & below	***Reference***	27.2
	Some college		15.3
	Associate's degree		15.0
	Bachelor's degree		23.0
	Master's degree & above		19.2
Family job status—			**99.7**
FT	***0 adults working FT***	***Reference***	55.2
	1 adult working FT		29.1
	2 adults working FT		13.7
	3+ adults working FT		1.8
			97.6
BMI	Underweight		1.0
	Healthy weight		23.0
	Overweight		34.6
	Obese	***Reference***	39.0

Research Question 1: To what extent is healthcare access (wellness visits and insurance status) a predictor of the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI)?

H_{01}: Healthcare access (wellness visits and insurance status) does not predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI).

H_{A1}: Healthcare access (wellness visits and insurance status) does predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI).

Research Question 2: To what extent are health behavior factors (alcohol use, and physical activity) a predictor of the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI)?

H_{02}: Health behavior factors (alcohol use and physical activity) does not predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI).

H_{A2}: Health behavior factors (drug use, tobacco use, physical activity, and immunization) does predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI).

The analysis output sample size was 14,575 with 1,380 missing cases. The Block 0 contains the intercept only model with no predictor variables added. The model predicted 100% of the Excellent/ Very Good health status and did not predict any of the Other health status group resulting in the intercept model accuracy of 56.6%. The intercept only model for the Wald's was statistically significant, and the regression slope (β) is negative.

Block 1 of the model with the four predictor variables (wellness visits, health insurance status, alcohol use, and physical activity) added to the model had the following results χ^2 (9, N =14,575) = 1,582.82, $p < .001$. The Hosmer and Lemeshow test or a "goodness-of-fit" test was .690, and anything over .05 indicates the model is a good fit for the analysis. The BLR is not linear so pseudo R^2 are used, and Cox & Snell & Nagelkerke R Square respectively indicates an approximate variance of 10.0%- 13.8% of the DV is explained by the IV's and 86.2% - 90% of the variance of the DV cannot be explained by the IV's. The Block 1 Classification Table indicates with the four independent variables in the model 44.4% of the Excellent/ Very Good health status was predicted correctly, and this is considered the sensitivity of the model. The positive predictive value of this model was 63.72% and the negative predictive value was 65.46% and the total predictions of health status outcome was 64.9% (Laerd Statistics, 2017). The specificity result showed the model correctly predicted 80.6% of participants that selected the reference group (Other health status), and the Block 1 model prediction improved 8.3 points to 64.9 {Overall percentage: Block 0 = 56.6% & Block 1 = 64.9%}.

The *Wald's* test, *S.E.*, the unstandardized *Beta*, *df*, p-value, *Exp* (β)/ Odds ratio, and Confidence Intervals for the four independent variables (wellness visits, insurance status, alcohol use & physical activity) for RQ1 and RQ2, are found in Table 10 below. The results were all statistically significant ($p < .001$), so the Ho is rejected for RQ1 and RQ2.

The result interpretations below focus on the probability of the Expected Logit (β) and Exp (β) or Odds Ratio for the four independent variables controlling for the seven sociodemographic variables and holding all others constant.

- <u>Wellness Visits (Yes):</u> For every unit increase in the participant going to a wellness visit, the Excellent/ Very Good health status variable log odds increase was 0.42 when keeping all others constant. Participants that had wellness visits had 1.52 times higher odds to select Excellent/ Very Good health status with 95% CI [1.38, 1.66].
- <u>Insurance Status (Yes):</u> For every unit increase in the participant having insurance, the Excellent/ Very Good health status variable log odds increase was 0.43 when keeping all others constant. Participants that had insurance had 1.54 times higher odds to select Excellent/ Very Good health status with 95% CI [1.27, 1.86].

- Physical Activity (PA) met for Strengthening: For every unit increase in the participant PA for strengthening, the Excellent/ Very Good health status log odds increase was 0.50 when keeping all others constant. Participants that had strengthening PA had 1.65 times higher odds to select Excellent/ Very Good health status with 95% CI [1.44, 1.89].
- PA met for Aerobics: For every unit increase in aerobic PA, the Excellent/ Very Good health status variable log odds increase was 0.78 when keeping all others constant. Participants that had aerobic PA had 2.18 times higher odds to select Excellent/ Very Good health status with 95% CI [2.01, 2.37].
- PA met for Both Strengthening and Aerobics: For every unit increase in the participant going to a wellness visit, the Excellent/ Very Good health status log odds increase was 1.32 when keeping all others constant. Participants that had both strengthening and aerobic PA had 3.75 times higher odds to select Excellent/ Very Good health status with 95% CI [3.40, 4.15].
- Current Infrequent AD: For every unit increase in the participant identifying as a current infrequent AD, the Excellent/ Very Good health status variable log odds increase was 0.23 when keeping all others constant. Participants that were current infrequent AD had 1.25 times higher odds to select Excellent/ Very Good health status with 95% CI [1.12, 1.40].
- Current Light AD: For every unit increase in the participant identifying as a current light AD, the Excellent/ Very Good health status variable log odds increase was 0.65 when keeping all others constant. Participants that were

current light AD had 1.91 times higher odds to select Excellent/ Very Good health status with 95% CI [1.75, 2.10].

- Current Moderate AD: For every unit increase in the participant identifying as a current moderate AD, the Excellent/ Very Good health status variable log odds increase was 0.91 when keeping all others constant. Participants that were current moderate AD had 2.50 times higher odds to select Excellent/ Very Good health status with 95% CI [2.25, 2.77].
- Current Heavy AD: For every unit increase in the participant identifying as a current heavy AD, the Excellent/ Very Good health status variable log odds increase was 0.60 when keeping all others constant. Participants that were current heavy AD had 1.83 times higher odds to select Excellent/ Very Good health status with 95% CI [1.58, 2.11].

Table 11

Binary Logistic Regression With Independent Variables Controlling for Covariates

								95% C.I.for EXP(B)	
		β	S.E.	Wald	*df*	Sig.	Exp(β)	Lower	Upper
Step 1 [a]	Was last visit a wellness visit (Yes)	.415	.047	77.800	1	< .001	1.515	1.381	1.662
	Health insurance (Yes)	.430	.098	19.096	1	< .001	1.537	1.268	1.864
	No physical activity (PA)			797.449	3	< .001			
	PA met for strengthening	.503	.069	52.467	1	< .001	1.653	1.443	1.894
	PA met for aerobic	.780	.043	332.875	1	< .001	2.182	2.006	2.372
	PA met for aerobic and strengthening	1.323	.051	674.058	1	< .001	3.754	3.397	4.148
	Former alcohol drinker (AD)			384.290	4	< .001			
	Current infrequent AD	.226	.055	16.580	1	< .001	1.253	1.124	1.397
	Current light AD	.648	.045	204.854	1	< .001	1.912	1.750	2.090
	Current moderate AD	.914	.053	294.047	1	< .001	2.493	2.246	2.767
	Current heavy AD	.601	.075	64.687	1	< .001	1.825	1.576	2.113
	Constant	-1.883	.108	302.765	1	< .001	.152	1.381	1.662

[a]. Variable(s) entered on Step 1: Wellness visits, Insurance status, Alcohol use, and Physical Activity

Block 2 of the model has both the four predictor variables (wellness visits, health insurance status, alcohol use, and physical activity) and the seven covariates (race/ethnicity, age, sex, marital status, education, family job status, and BMI) added to the model, with the following results χ^2 (21, *N*=14,575) = 956.51, $p < .001$. The Hosmer and Lemeshow test or a “goodness-of-fit” test was .236, which indicates the model is a good fit. The Cox & Snell & Nagelkerke R Square respectively indicates an approximate variance of 16.0%- 21.4% of the DV is explained by the IV’s and 78.6% - 84% of the variance of the DV cannot be explained by the IV's. The Block 2 Classification Table indicates with the four independent variables in the model combined with the seven covariates indicate 55.1% of the Excellent/ Very Good health status was predicted correctly, and this is considered the sensitivity of the model. The positive predictive value of this model was 65.87% and the negative predictive value was 69.45% and the total predictions of health status outcome was 68.2%. The specificity result showed the model correctly predicted 78.1% of participants that selected the reference group (Other health status), and the Block 2 model prediction improved 11.6 points to 68.2{Overall percentage: Block 0 =56.6% & Block 2 = 68.2%}.

The *Wald's* test, *S.E.*, the unstandardized *Beta*, *df*, p-value, *Exp* (β)/ Odds ratio, and Confidence Intervals for the four predictor variables (wellness visits, insurance status, alcohol use & physical activity) and the seven covariates (race/ethnicity, age, sex, marital status, education, family job status, and BMI) for RQ1 and RQ2, are found in Table 12 below. All of the results were statistically significant with the exception of Insurance Status *p* = .482, BMI-Underweight *p* = .994, NH Asian *p*= .056, and NH American Indian/ Alaskan *p* = .767.

The result interpretations below focus on the probability of the Expected Logit (β) and Exp (β) or Odds Ratio for the four independent variables plus the seven sociodemographic variables and holding all others constant.

- <u>Wellness Visits (Yes):</u> For every unit increase in the participant going to a wellness visit, the Excellent/ Very Good health status variable log odds increase was 0.50 when keeping all others constant. Participants that had wellness visits had 1.64 times higher odds to select Excellent/ Very Good health status with 95% CI [1.49, 1.81].

- Insurance Status (Yes): The insurance status was not statistically significant with a p-value = .482.
- Physical Activity (PA) met for Strengthening: For every unit increase in the participant PA for strengthening, the Excellent/ Very Good health status variable log odds increase was 0.41 when keeping all others constant. Participants that had strengthening PA had 1.51 times higher odds to select Excellent/ Very Good health status with 95% CI [1.31, 1.74].
- PA met for Aerobics: For every unit increase in the participant PA for aerobics, the Excellent/ Very Good health status variable log odds increase was 0.65 when keeping all others constant. Participants that had aerobic PA had 1.92 times higher odds to select Excellent/ Very Good health status with 95% CI [1.76, 2.10].
- PA met for Both Strengthening and Aerobics: For every unit increase in the participant PA for both strengthening and aerobics, the Excellent/ Very Good health status variable log odds increase was 1.12 when keeping all others constant. Participants that had both strengthening and aerobic PA had 3.07 times higher odds to select Excellent/ Very Good health status increase by a factor of 3.75 with 95% CI [2.77, 3.42].
- Current Infrequent AD: For every unit increase in the participant identifying as a current infrequent AD, the Excellent/ Very Good health status variable

log odds increase was 0.16 when keeping all others constant. Participants that were current infrequent AD had 1.18 times higher odds to select Excellent/ Very Good health status with 95% CI [1.05, 1.32].

- Current Light AD: For every unit increase in the participant identifying as a current light AD, the Excellent/ Very Good health status variable log odds increase was 0.49 when keeping all others constant. Participants that were current light AD had 1.64 times higher odds to select Excellent/ Very Good health status with 95% CI [1.49, 1.80].
- Current Moderate AD: For every unit increase in the participant identifying as a current moderate AD, the Excellent/ Very Good health status variable log odds increase was 0.74 when keeping all others constant. Participants that were current moderate AD had 2.10 times higher odds to select Excellent/ Very Good health status with 95% CI [1.87, 2.35].
- Current Heavy AD: For every unit increase in the participant identifying as a current heavy AD, the Excellent/ Very Good health status variable log odds increase was 0.41 when keeping all others constant. Participants that were current heavy AD had 1.51 times higher odds to select Excellent/ Very Good health status with 95% CI [1.30, 1.76].
- BMI- Underweight: The BMI-Underweight was not statistically significant with a p-value = .994.
- BMI-Healthy Weight: For every unit increase in the participant having a healthy weight, the Excellent/ Very Good health status variable log odds

increase was 0.63 when keeping all others constant. Participants that had a healthy weight had 1.88 times higher odds to select Excellent/ Very Good health status with 95% CI [1.71, 2.07].

- BMI- Overweight: For every unit increase in the participant being overweight, the Excellent/ Very Good health status variable log odds increase was 0.57 when keeping all others constant. Participants that were overweight had 1.77 times higher odds to select Excellent/ Very Good health status with 95% CI [1.63, 1.93].
- Married: For every unit increase in the married participant, the Excellent/ Very Good health status variable log odds increase was 0.10 when keeping all others constant. Married participants had 1.11 times higher odds to select Excellent/ Very Good health status with 95% CI [1.02, 1.20].
- Cohabitating: For every unit increase in the cohabitating participant, the Excellent/ Very Good health status variable log odds decrease was -0.34 when keeping all others constant. Participants that cohabitated had 0.72 times lower odds to select Excellent/ Very Good health status with 95% CI [0.59, 0.87].
- 1 Adult Working FT: For every unit increase in the participant that had 1 adult FT worker, the Excellent/ Very Good health status variable log odds increase was 0.45 when keeping all others constant. Participants that had 1 FT worker in the family had 1.57 times higher odds to select Excellent/ Very Good health status with 95% CI [1.42, 1.72].

- 2 Adults Working FT: For every unit increase in the participants that had 2 adult FT workers, the Excellent/ Very Good health status variable log odds increase was 0.60 when keeping all others constant. Participants that had 2 FT workers in the family had 1.83 times higher odds to select Excellent/ Very Good health status with 95% CI [1.60, 2.08].
- 3+ Adults Working FT: For every unit increase in the participants that had 3 or more adult FT workers, the Excellent/ Very Good health status variable log odds increase was 0.40 when keeping all others constant. Participants that had 3 or more FT workers in the family had 1.49 times higher odds to select Excellent/ Very Good health status with 95% CI [1.14, 1.96].
- Female: For every unit increase in the participant being a female, the Excellent/ Very Good health status variable log odds increase was 0.24 when keeping all others constant. Female participants had 1.27 times higher odds to select Excellent/ Very Good health status with 95% CI [1.18, 1.37].
- Age: 21-44: For every unit increase in the participant being age 21-44, the Excellent/ Very Good health status variable log odds decrease was -1.30 when keeping all others constant. Participants aged 21-44 had 0.27 times lower odds to select Excellent/ Very Good health status with 95% CI [0.12, 0.61].
- Age: 45-64: For every unit increase in the participant being age 45-64, the Excellent/ Very Good health status variable log odds decrease was -1.51 when keeping all others constant. Participants aged 45-64 had 0.22 times lower odds to select Excellent/ Very Good health status with 95% CI [0.10, 0.49].

- Age: 65+: For every unit increase in the participant being age 65+, the Excellent/ Very Good health status variable log odds decrease was -1.29 when keeping all others constant. Participants age 65+ had 0.28 times lower odds to select Excellent/ Very Good health status with 95% CI [0.12, 0.62].
- Some College: For every unit increase in participants with some college, the Excellent/ Very Good health status variable log odds increase was 0.27 when keeping all others constant. Participants that had some college had 1.31 times higher odds to select Excellent/ Very Good health status with 95% CI [1.17, 1.48].
- Associate’s Degree: For every unit increase in participants with a associate’s degree, the Excellent/ Very Good health status variable log odds increase was 0.27 when keeping all others constant. Participants that had an associate’s degree had 1.32 times higher odds to select Excellent/ Very Good health status with 95% CI [1.16, 1.47].
- Bachelor’s Degree: For every unit increase in participants with a bachelor’s degree, the Excellent/ Very Good health status variable log odds increase was 0.54 when keeping all others constant. Participants that had a bachelor’s degree had 1.72 times higher odds to select Excellent/ Very Good health status with 95% CI [1.56, 1.91].
- Master’s Degree & Above: For every unit increase in participants with a master’s degree & above, the Excellent/ Very Good health status variable log odds increase was 0.77 when keeping all others constant. Participants that had

a master's degree & above had 2.16 times higher odds to select Excellent/ Very Good health status with 95% CI [1.93, 2.42].

- NH Black/ African American: For every unit increase in NH Black/ African American participants, the Excellent/ Very Good health status variable log odds decrease was -0.57 when keeping all others constant. NH Black/ African American participants had 0.56 times lower odds to select Excellent/ Very Good health status with 95% CI [0.50, 0.64].
- Hispanic: For every unit increase in Hispanic participants, the Excellent/ Very Good health status variable log odds decrease was -0.55 when keeping all others constant. Hispanic participants had 0.58 times lower odds to select Excellent/ Very Good health status with 95% CI [0.51, 0.66].
- NH Asian: This was not statistically significant with a p-value = .056.
- NH American Indian/ Alaskan: This was not statistically significant with a p-value = .676.
- Other/ Mixed Races: For every unit increase in other/ mixed race participants, the Excellent/ Very Good health status variable log odds decrease was -0.46 when keeping all others constant. Other/ mixed race participants had 0.63 times lower odds to select Excellent/ Very Good health status with 95% CI [0.47, 0.85].

Table 12

Binary Logistic Regression With Independent and Covariate Variables

		B	S.E.	Wald	*df*	Sig.	Exp(B)	95% C.I. for EXP(B) Lower	Upper
Step 1 [a]	Was last visit a wellness visit (Yes)	.497	.049	103.127	1	< .001	1.644	1.494	1.809
	Health insurance (Yes)	.073	.103	.495	1	**.482**	1.075	.878	1.316
	No physical activity (PA)			508.174	3	< .001			
	PA met for strengthening	.414	.072	32.962	1	< .001	1.513	1.314	1.743
	PA met for aerobic	.652	.045	213.356	1	< .001	1.919	1.758	2.094
	PA met for aerobic and strengthening	1.123	.054	432.867	1	< .001	3.074	2.766	3.418
	Former alcohol drinker (AD)			204.180	4	< .001			
	Current infrequent AD	.162	.058	7.888	1	.005	1.176	1.050	1.317
	Current light AD	.493	.048	104.513	1	< .001	1.638	1.490	1.800
	Current moderate AD	.740	.057	166.735	1	< .001	2.097	1.874	2.346
	Current heavy AD	.410	.079	26.998	1	< .001	1.507	1.291	1.759
	BMI (Obese)			237.476	3	< .001			
	Underweight	.001	.204	.000	1	**.994**	1.001	.671	1.495
	Healthy weight	.631	.049	163.805	1	< .001	1.880	1.707	2.071
	Overweight	.573	.043	176.616	1	< .001	1.774	1.630	1.931
	Married status (neither)			23.056	2	< .001			
	Married	.101	.041	6.177	1	.013	1.107	1.022	1.199
	Cohabitating	**-.335**	.099	11.493	1	< .001	.715	.589	.868
	0 adults working FT			113.564	3	< .001			
	1 adult working FT	.448	.049	85.021	1	< .001	1.565	1.423	1.722
	2 adult working FT	.602	.066	82.949	1	< .001	1.826	1.604	2.079
	3+ adult working FT	.400	.140	8.211	1	.004	1.492	1.135	1.963
	Sex—Women	.241	.039	39.062	1	< .001	1.273	1.180	1.373
	Age: 18–20			38.722	3	< .001			
	Age: 21–44	**-1.305**	.412	10.050	1	.002	.271	.121	.608
	Age: 45–64	**-1.511**	.410	13.590	1	< .001	.221	.099	.493
	Age: 65+	**-1.290**	.410	9.877	1	.002	.275	.123	.615
	High school & below			199.833	4	< .001			
	Some college	.272	.060	20.780	1	< .001	1.313	1.168	1.476
	Associate’s degree	.270	.060	19.869	1	< .001	1.309	1.163	1.474
	Bachelor’s degree	.541	.054	99.785	1	< .001	1.718	1.545	1.910
	Master’s degree & above	.770	.058	175.662	1	< .001	2.160	1.928	2.421
	Non-Hispanic (NH) White			135.653	5	< .001			
	NH Black/African American	**-.573**	.063	82.531	1	< .001	.564	.498	.638
	Hispanic	**-.547**	.068	65.538	1	< .001	.579	.507	.661
	NH Asian	-.179	.094	3.638	1	**.056**	.836	.696	1.005
	NH American Indian/ Alaskan	-.071	.239	.088	1	**.767**	.932	.583	1.489
	Other/mixed races	**-.464**	.151	9.412	1	.002	.629	.468	.846
	Constant	-1.062	.425	6.237	1	.013	.346		

[a] Variable(s) entered on Step 1: Categorical body mass index, public use, Sample adult's (SA) current marital status, Number of adults in sample adult's family who are working full-time, Sex of SA, Age of SA by Census brackets, Education, Race/Ethnicity.

Analysis for Research Question 3

The final research question focused the BLR data analysis to analyze how the seven sociodemographic covariates (race/ethnicity, age, sex, marital status, education, family job status, and BMI) influenced the binary health status (Excellent/Very Good or Other). Please see Table 12 below for the results and the RQ3 summary.

Research Question 3: To what extent are sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI) a predictor of the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States?

H_{03}: Sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI) does not predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States.

H_{A3}: Sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI) does predict the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States.

The analysis output sample size was 15,067 with 888 missing cases. The Block 0 contains the intercept only model with no covariate variables added. The model predicted 100% of the Excellent/ Very Good health status and did not predict any of the Other health status group resulting in the intercept model accuracy of 56.7%. The intercept only model for the Wald's was statistically significant, and the regression slope (β) is negative.

Block 1 of the model has only the seven covariate variables (race/ethnicity, age, sex, marital status, education, family job status, and BMI) and showed the following results χ^2 (21, N =15,067) = 1,664.03, $p < .001$. The Hosmer and Lemeshow test or a "goodness-of-fit" test was .125, and anything over .05 indicates the model is a good fit for the analysis. The BLR is not linear so pseudo R^2 are used, and Cox & Snell & Nagelkerke R Square respectively indicates an approximate variance of 10.5%- 14.0% of the health status outcome is explained by the sociodemographic covariates and 86.0% - 89.5% of the variance of the health status outcome cannot be explained by the covariates. The Block 1 Classification Table indicates 49.8% of the Excellent/ Very Good health status was predicted correctly, and this is considered the sensitivity of the model. The positive predictive value of this model was 61.34% and the negative predictive value was 66.53% and the total predictions of health status outcome was 64.7%. The specificity result showed the model correctly predicted 76.0% of participants that selected the reference group (Other health status), and the Block 1 model prediction improved 8 points to 64.7 {Overall percentage: Block 0 = 56.7% & Block 1 = 64.7%}.

The *Wald's* test, *S.E.*, the unstandardized *Beta*, *df*, p-value, *Exp* (β)/ Odds ratio, and Confidence Intervals for the covariate variables (race/ethnicity, age, sex, marital status, education, family job status, and BMI) for RQ3 are found in Table 13 below. The results for the six covariates were statistically significant excluding the sex variable. The results were BMI-Underweight *p* = .745, Females *p*= .166, NH American Indian/ Alaskan *p* = .245, so the Ho is rejected for RQ3.

The result interpretations below focus on the probability of the Expected Logit (β) and Exp (β) or Odds Ratio for the four independent variables controlling for the seven sociodemographic variables and holding all others constant.

- <u>BMI- Underweight: </u>The BMI-Underweight was not statistically significant with a p-value = .745.
- <u>BMI-Healthy Weight: </u>For every unit increase in the participant having a healthy weight, the Excellent/ Very Good health status variable log odds increase was 0.77 when keeping all others constant. Participants that had a healthy weight had 2.16 times higher odds to select Excellent/ Very Good health status with 95% CI [1.97, 2.36].
- <u>BMI- Overweight: </u>For every unit increase in the participant being overweight, the Excellent/ Very Good health status variable log odds increase was 0.68 when keeping all others constant. Participants that were overweight had 1.97 times higher odds to select Excellent/ Very Good health status with 95% CI [1.81, 2.13].
- <u>Married: </u>For every unit increase in the married participant, the Excellent/ Very Good health status variable log odds increase was 0.11 when keeping all others constant. Married participants had 1.11 times higher odds to select Excellent/ Very Good health status with 95% CI [1.03, 1.12].

- Cohabitating: For every unit increase in the cohabitating participant, the Excellent/ Very Good health status variable log odds decrease was -0.30 when keeping all others constant. Participants that cohabitated had 0.74 times lower odds to select Excellent/ Very Good health status with 95% CI [0.62, 0.89].
- 1 Adult Working FT: For every unit increase in the participant that had 1 adult FT worker, the Excellent/ Very Good health status variable log odds increase was 0.47 when keeping all others constant. Participants that had 1 FT worker in the family had 1.60 times higher odds to select Excellent/ Very Good health status with 95% CI [1.46, 1.75].
- 2 Adults Working FT: For every unit increase in the participants that had 2 adult FT workers, the Excellent/ Very Good health status variable log odds increase was 0.63 when keeping all others constant. Participants that had 2 FT workers in the family had 1.87 times higher odds to select Excellent/ Very Good health status with 95% CI [1.65, 2.11].
- 3+ Adults Working FT: For every unit increase in the participants that had 3 or more adult FT workers, the Excellent/ Very Good health status variable log odds increase was 0.39 when keeping all others constant. Participants that had 3 or more FT workers in the family had 1.49 times higher odds to select Excellent/ Very Good health status with 95% CI [1.13, 1.91].
- Female: The sex variable was not statistically significant and the female p-value = .166.

- Age: 21-44: For every unit increase in the participant being age 21-44, the Excellent/ Very Good health status variable log odds decrease was -1.29 when keeping all others constant. Participants aged 21-44 had 0.28 times lower odds to select Excellent/ Very Good health status with 95% CI [0.13, 0.61].
- Age: 45-64: For every unit increase in the participant being age 45-64, the Excellent/ Very Good health status variable log odds decrease was -1.61 when keeping all others constant. Participants aged 45-64 had 0.20 times lower odds to select Excellent/ Very Good health status with 95% CI [0.09, 0.44].
- Age: 65+: For every unit increase in the participant being age 65+, the Excellent/ Very Good health status variable log odds decrease was -1.48 when keeping all others constant. Participants age 65+ had 0.23 times lower odds to select Excellent/ Very Good health status with 95% CI [0.10, 0.50].
- Some College: For every unit increase in participants with some college, the Excellent/ Very Good health status variable log odds increase was 0.37 when keeping all others constant. Participants that had some college had 1.44 times higher odds to select Excellent/ Very Good health status with 95% CI [1.29, 1.61].
- Associate's Degree: For every unit increase in participants with a associate's degree, the Excellent/ Very Good health status variable log odds increase was 0.36 when keeping all others constant. Participants that had an associate's degree had 1.43 times higher odds to select Excellent/ Very Good health status with 95% CI [1.28, 1.60].

- Bachelor's Degree: For every unit increase in participants with a bachelor's degree, the Excellent/ Very Good health status variable log odds increase was 0.76 when keeping all others constant. Participants that had a bachelor's degree had 2.13 times higher odds to select Excellent/ Very Good health status with 95% CI [1.93, 2.36].
- Master's Degree & Above: For every unit increase in participants with a master's degree & above, the Excellent/ Very Good health status variable log odds increase was 1.06 when keeping all others constant. Participants that had a master's degree & above had 2.90 times higher odds to select Excellent/ Very Good health status with 95% CI [2.61, 3.22].
- NH Black/ African American: For every unit increase in NH Black/ African American participants, the Excellent/ Very Good health status variable log odds decrease was -0.61 when keeping all others constant. NH Black/ African American participants had 0.54 times lower odds to select Excellent/ Very Good health status with 95% CI [0.48, 0.61].
- Hispanic: For every unit increase in Hispanic participants, the Excellent/ Very Good health status variable log odds decrease was -0.56 when keeping all others constant. Hispanic participants had 0.56 times lower odds to select Excellent/ Very Good health status with 95% CI [0.49, 0.63].
- NH Asian: For every unit increase in NH Asian participants, the Excellent/ Very Good health status variable log odds decrease was -0.33 when keeping

all others constant. NH Asian participants had 0.72 times lower odds to select Excellent/ Very Good health status with 95% CI [0.60, 0.86].

- NH American Indian/ Alaskan: This was not statistically significant with a p-value = .245.
- Other/ Mixed Races: For every unit increase in other/ mixed race participants, the Excellent/ Very Good health status variable log odds decrease was -0.49 when keeping all others constant. Other/ mixed race participants had 0.61 times lower odds to select Excellent/ Very Good health status with 95% CI [0.46, 0.81].

Table 13

Binary Logistic Regression Covariates Only

		B	S.E.	Wald	*df*	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 [a]	BMI (Obese)			380.418	3	<.001			
	Underweight	**-.062**	.191	.106	1	**.745**	.940	.647	1.366
	Healthy weight	.768	.047	271.082	1	< .001	2.155	1.966	2.361
	Overweight	.675	.041	272.017	1	< .001	1.965	1.813	2.129
	Marital status (neither)			23.017	2	< .001			
	Married	.105	.039	7.311	1	.007	1.111	1.029	1.198
	Cohabitation	**-.296**	.093	10.152	1	.001	.744	.620	.892
	0 adults working FT			137.494	3	< .001			
	1 adults working FT	.467	.046	103.030	1	< .001	1.596	1.458	1.746
	2 adults working FT	.626	.063	99.726	1	< .001	1.870	1.653	2.114
	3+ adults working FT	.385	.134	8.266	1	.004	1.469	1.130	1.910
	Female	.049	.036	1.918	1	**.166**	1.051	.980	1.127
	Age: 18–20			47.502	3	< .001			
	Age: 21–44	**-1.290**	.404	10.197	1	.001	.275	.125	.607
	Age: 45–64	**-1.608**	.402	15.958	1	< .001	.200	.091	.441
	Age: 65+	**-1.475**	.403	13.391	1	< .001	.229	.104	.504
	High school & below			447.122	4	< .001			
	Some college	.366	.057	41.783	1	< .001	1.443	1.291	1.612
	Associate’s degree	.358	.057	38.889	1	< .001	1.431	1.279	1.601
	Bachelor’s degree	.758	.051	221.211	1	< .001	2.134	1.931	2.358
	Master’s degree	1.064	.054	384.732	1	< .001	2.899	2.607	3.224
	Non-Hispanic (NH) White			180.141	5	< .001			
	NH Black/ African American	**-.614**	.060	103.905	1	< .001	.541	.481	.609
	Hispanic	**-.585**	.064	84.623	1	< .001	.557	.492	.631
	NH Asian	**-.332**	.089	13.839	1	< .001	.718	.603	.855
	NH American Indian/ Alaskan	**-.262**	.225	1.351	1	**.245**	.770	.495	1.197
	Other/mixed race	**-.491**	.144	11.587	1	< .001	.612	.461	.812
	Constant	.127	.404	.098	1	.754	1.135		

a. Variable(s) entered on Step 1: Categorical body mass index, public use, Sample adult's current marital status, Number of adults in sample adult's family who are working full-time, Sex of Sample Adult, Age of SA by Census brackets, NEWEDU, NEWRACE.

Summary

The purpose of this study was to examine the relationship and impact that healthcare access, health behaviors, and sociodemographic factors have on health equity outcome represented by self-reported health status for adult cardiometabolic NHIS 2020 survey participants. A Chi-Square test was performed, and all 12 variables showed associations with physical activity having a large effect size, followed by alcohol use, race, and education with a medium effect size respectively. The variables age, marital status, and family job status had small effect sizes. Finally, wellness visits, insurance status, and sex had very small effect sizes. The null hypothesis was rejected for RQ1, RQ2, and RQ3 and the alternative hypothesis was favored. Section 3 outlined the descriptive statistics and BLR results which concludes that healthcare access, health behaviors, and sociodemographic factors significantly predicted health equity outcomes represented by Excellent/ Very Good versus Other (self-reported health status).

In Section 4, the interpretation of the results will be described along with any unique points of interest. The limitations of the study, recommendations for further research, implications for professional practice, and social change concepts will be explored in this final section.

Section 4: Application to Professional Practice and Implications for Social Change

Introduction

The leading cause of morbidity and mortality in the United States is cardiovascular-related. The cost estimates for medical care, loss of productivity, and premature death are upwards of $135 billion (Turner, 2018). There is very little literature analyzing cardiovascular health risk factors, sociodemographic factors, and cardiometabolic conditions (hypertension, high cholesterol, coronary heart disease, and diabetes) collectively (Lopez-Neyman et al., 2022). Most research studies select only one of these conditions versus looking at them collectively, and that was the primary aim of this research.

Health equity outcomes research is growing and continues to have a significant impact on population health education, intervention strategies, policy, and practitioner applications. The research problem addressed in this study involved using the NHIS 2020 secondary dataset to analyze how health equity outcomes (health status) are influenced by healthcare access, health behaviors, and socioeconomic factors predictor variables. The BLR was used to analyze all three research questions, and the null hypothesis was rejected for all three, indicating that healthcare access, health behaviors, and sociodemographic factors have a statistically significant and a predominantly medium effect size on the health status outcome variable.

Interpretation of the Findings

The findings extend the knowledge of the discipline and fill a gap in the research while addressing key health factors and sociodemographic factors that influence self-reported health status outcomes. The target population of adults with cardiometabolic conditions outlined in this research showed that health behaviors had the highest influence on positive health status, followed by the sociodemographic factors, and finally the healthcare access factors. In this study sample, the healthcare access variables showed that 96% of participants had insurance and 81% had wellness visits. The health behaviors provided the most meaningful and highest odds of a survey participant selecting excellent/very good health status, with 46% who were physically active and 51% of the sample who did not have any physical activity. Data for current alcohol drinker status showed that 62% of the sample were drinkers. Sociodemographic data showed that 73% of the target sample were college educated, half of the sample were married, 74% were overweight and obese, and 55% had zero adults working full time in the family. The sample population's race and sex percentages closely mirrored U.S. Census data for 2020 (U.S. Census Bureau, 2023). According to Humes (2023), data from NHIS years 2007–2018 indicated that 111,625 out of 357,714 (31%) participants were 60+ years of age during this 10-year timeframe. This NHIS 2020 study sample did uniquely reflect an unusually high amount of 65+ participants at 50% in comparison to the 31% for the previous 10-year average. The 2020 U.S. Census stated that 16% of the population were 65+ (U.S. Census Bureau, 2023). Finally, 43% of the targeted sample self-reported excellent/very good health status and 57% reported other.

Research Question 1: To what extent are wellness visits and insurance status a predictor of the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI)?

Research Question 2: To what extent are alcohol use and physical activity a predictor of the health equity outcome as measured by health status in adults with cardiometabolic conditions in the United States, while controlling for sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI)?

The binary logistic regression Block 1 determined that the four independent variables were all statistically significant while controlling for the seven covariates. The strongest predictors by odds ratio were physical activity, specifically physical activity with both strengthening and aerobics. The current moderate alcohol drinking status had the second highest odds of selecting the health status outcome (excellent/very good) status. Block 2 determined that all variables were statistically significant except for insurance status, being underweight, sex, NH Asian, and NH American Indian/Alaskan. Physical activity with strengthening and education, specifically master's degree and above, bachelor's degree, and current moderate AD, had the highest odds ratio when the four independent variables combined with the covariates were analyzed.

Research Question 3: To what extent are sociodemographic factors (race/ethnicity, age, sex, marital status, education, family job status, and BMI) a predictor of the health equity outcome health status in adults with cardiometabolic conditions in the United States?

The BLR Block 1 determined that the seven covariate sociodemographic variables were all statistically significant except for being underweight, sex (female), and NH American Indian/Alaskan. The strongest predictors by odds ratio in descending order were having a master's degree and above, having a bachelor's degree, BMI—healthy weight and overweight, and two full-time workers in the family. This parallels the medium effect size for the sociodemographic factors, which were race/ethnicity, education, and BMI. The covariates with the smaller effect sizes were sex, age, marital status, and family job status.

Limitations of the Study

A limitation of this study pertained to participation, which was only available to individuals in the United States who were members of the target population, which was identified as adults who reported having a cardiometabolic condition (hypertension, coronary heart disease, cholesterol, & diabetes). Another limitation of this study was the COVID-19 government-required lockdown and pandemic that started in the United States in March 2020, which caused most of the interviews to be conducted by phone instead of face to face. This was the first time in NHIS history that the overwhelming majority of surveys were conducted in this manner. This survey's response data collection and analysis were also susceptible to nonresponse bias and recall bias (Last, 2000). Recall bias is a systematic error in research caused by differences in the accuracy or completeness of the recollections of study participants regarding events or experiences from the past (Last, 2000). The study results cannot establish cause and effect and cannot generalize for other countries because the sample is a representation of the United States.

Recommendations

Further research is needed to continue work to improve cardiovascular-related morbidity and mortality from the collective cardiometabolic disease perspective. The first research recommendation is to include a mixed methods study design to capture additional data from target group ages 18+ thru age 65. The results of this study showed that 50% of the entire sample were age 65+, and 85% were aged 45 and up. This reflects an above-average cohort, according to research that addressed NHIS descriptive statistics for years 2007–2018, which showed that older adults 60+ years of age represented 31% of the participants during that timeframe (Humes, 2023). The typical reasons why an older sample group would dominate this survey in 2020 are ambiguous because the entire country experienced a mandatory lockdown, including a work-from-home requirement, for most of 2020. Younger workers would have had an increased opportunity to complete this survey because it was conducted over the phone instead of in person.

The next recommendation is to include a longitudinal research design with the same variables to compare against these study results. The NHIS did have a small subcomponent (approximately 10,000) of individuals who participated in the NHIS 2019 who were contacted again for the NHIS 2020 to create unique access to longitudinal data.

The final recommendation is to conduct further research with healthcare access variables with a medium to large effect size because both wellness visits and insurance status had very small meaningfulness. This was possibly due to the fact that the majority of participants in this sample had health insurance and wellness visits that can be explained in part by the sample being predominantly White, college educated, and older.

Although it is common for health status to decline as individuals age, it is also typical that healthcare access increases due to more stability.

Implications for Professional Practice and Social Change

This research revealed that health behaviors have a significant impact on health status. Healthy People 2030 details how important health equity will be this decade with the primary focus on SDOH and overall improvement in healthcare access and health behaviors, while considering the influences of sociodemographic factors. Public health practitioners and other population health practitioners should include other stakeholders and continue to develop or resume interventional work targeting adults with cardiometabolic conditions and positive health behavior lifestyle modifications.

This research may promote positive social change because the findings can be utilized by multiple stakeholders interested in measuring health equity outcomes among adults with cardiometabolic conditions collectively. Public health educators, communication specialists, policy makers, clinicians, patient advocacy groups, senior care practitioners, and other healthcare practitioners should utilize the findings of my research to help with public health education campaigns, policy research, and any organization that focuses on cardiovascular-related disease improvement.

Conclusion

In conclusion, this research has provided the unique perspective of a cross-sectional research study regarding health equity outcomes highlighting self-reported health status. The ABM conceptual framework captured the essence of this research with identical terms that describe how a target group, healthcare access, health behaviors, and socioeconomic factors influence health equity. It is imperative that diverse studies of primary and secondary data are conducted to expand knowledge to reduce cardiovascular-related deaths.

References

Andersen, R. M. (1995). Revisiting the behavioral model and access to medical care: Does it matter? *Journal of Health and Social Behavior*, *36*(1), 1–10.

Andersen, R. M., & Davidson, P. L. (2007). Improving access to care in America: Individual and contextual indicators. In R. M. Andersen, T. H. Rice, & G. F. Kominski (Eds.), *Changing the U.S. health care system: Key issues in health services policy and management* (pp. 3–31). Jossey-Bass.

Armstrong, B. G., & Sloan, M. (1989). Ordinal regression models for epidemiologic data. *American Journal of Epidemiology*, *129*(1), 191–204. https://doi.org/10.1093/oxfordjournals.aje.a115109

Babitsch, B., Gohl, D., & von Lengerke, T. (2012). Re-revisiting Andersen's behavioral model of health services use: A systematic review of studies from 1998–2011. *Psycho-Social Medicine*, *9*, Article 11. https://doi.org/10.3205/psm000089

Bailit, M., & Kanneganti, D. (2022, March 21). *A typology for health equity measures.* https://www.healthaffairs.org/do/10.1377/forefront.20220318.155498

Bhandari, P. (2022a, November 30). *External validity: Definition, types, threats & examples.* Scribbr. https://www.scribbr.com/methodology/external-validity/

Bhandari, P. (2022b, November 11). *Type I & Type II errors: Differences, examples, visualizations.* Scribbr. https://www.scribbr.com/statistics/type-i-and-type-ii-errors/

Bobbitt, Z. (2021, September 30). *How to interpret Cramer's V (with examples).* Statology. https://www.statology.org/interpret-cramers-v/

Borsky, A., Zhan, C., Miller, T., Ngo-Metzger, Q., Bierman, A. S., & Meyers, D. (2018). Few Americans Receive all high-priority, appropriate clinical preventive services. *Health Affairs (Project Hope)*, *37*(6), 925–928. https://doi.org/10.1377/hlthaff.2017.1248

Bramlett, M. D., Dahlhamer, J. M., & Bose, J. (2021, September). *Weighting procedures and bias assessment for the 2020 National Health Interview Survey.* https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Dataset_Documentation/NHIS/2020/nonresponse-report-508.pdf

Centers for Disease Control and Prevention. (n.d.). *Health equity in Healthy People 2030.* Home of the Office of Disease Prevention and Health Promotion—Health.gov. https://health.gov/healthypeople/priority-areas/health-equity-healthy-people-2030

Centers for Disease Control and Prevention. (2018). *National Health Interview Survey: Survey description.* https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Dataset_Documentation/NHIS/2017/srvydesc.pdf

Centers for Disease Control and Prevention. (2022a, August 8). *Health status.* https://www.cdc.gov/nchs/hus/topics/health-status.htm

Centers for Disease Control and Prevention. (2022b, March 4). *Healthy people—Healthy People 2020 overview of health disparities.* https://www.cdc.gov/nchs/healthy_people/hp2020/health-disparities.htm

Centers for Disease Control and Prevention. (2022c, October 14). *Heart disease facts.* https://www.cdc.gov/heartdisease/facts.htm

Centers for Disease Control and Prevention. (2022d, July 12). *Heart disease resources*. https://www.cdc.gov/heartdisease/about.htm

Cheng, X., Ma, T., Ouyang, F., Zhang, G., & Bai, Y. (2022). Trends in the prevalence of cardiometabolic multimorbidity in the United States, 1999–2018. *International Journal of Environmental Research and Public Health*, *19*(8), Article 4726. https://doi.org/10.3390/ijerph19084726

Cho, H., Wang, Z., Yabroff, K. R., Liu, B., McNeel, T., Feuer, E. J., & Mariotto, A. B. (2022). Estimating life expectancy adjusted by self-rated health status in the United States: National Health Interview Survey linked to the mortality. *BMC Public Health*, *22*(1), Article 141. https://doi.org/10.1186/s12889-021-12332-0

Crowson, M. (2019, June 21). *Binary logistic regression using SPSS (June 2019)* [Video]. YouTube. https://www.youtube.com/watch?v=cpWSSJHuT2s

Davis, R. (2015, June). *Measuring what works to achieve health equity: Metrics for the determinants of health.* Prevention Institute. https://www.preventioninstitute.org/publications/measuring-what-works-achieve-health-equity-metrics-determinants-health

Deshpande, A. D., McQueen, A., & Coups, E. J. (2012). Different effects of multiple health status indicators on breast and colorectal cancer screening in a nationally representative US sample. *Cancer Epidemiology*, *36*(3), 270–275. https://doi.org/10.1016/j.canep.2011.10.001

Dover, D. C., & Belon, A. P. (2019). Correction to: The health equity measurement framework: A comprehensive model to measure social inequities in health.

International Journal for Equity in Health, *18*(1). https://doi.org/10.1186/s12939-019-0949-7

Dyck, L. A., Snelling, S., Morrison, V., Haworth-Brockman, M., & Atkinson, D. (2018). Equity reporting: A framework for putting knowledge mobilization and health equity at the core of population health status reporting. *Health Promotion and Chronic Disease Prevention in Canada*, *38*(3), 116-124. https://doi.org/10.24095/hpcdp.38.3.02

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*, 1149-1160. https://www.psychologie.hhu.de/arbeitsgruppen/allgemeine-psychologie-und-arbeitspsychologie/gpower

Frankfort-Nachimas, C., & Nachimas, D. (2008). *Research methods in the social sciences* (7th ed.) New York, NY: Worth Publishers.

Greenacre, M. (2016). *Correspondence Analysis in Practice* (3rd ed.). Chapman and Hall/CRC. https://doi.org/10.1201/9781315369983

Hamad, R., & Galea, S. (2022). The Role of Health Care Systems in Bolstering the Social Safety Net to Address Health Inequities in the Wake of the COVID-19 Pandemic. *Journal of American Medical Association (JAMA)*, *328*(1), 17–18. https://doi.org/10.1001/jama.2022.10160

Heron, M., & Anderson, R. (2016). Changes in the leading cause of death: Recent patterns in heart disease and cancer mortality. Hyattsville, MD: *National Center* *for Health Statistics (NCHS) Data Brief,* (254). https://www.cdc.gov/nchs/data/databriefs/db254.pdf

Humes, L. E. (2023). U.S. population data on self-reported trouble hearing and hearing-aid use in adults: National health interview survey, 2007–2018. *Trends in Hearing, 27,* 233121652311609. https://doi.org/10.1177/23312165231160967

Iacobucci, D., Posavac, S. S., Kardes, F. R., Schneider, M., & Popovich, D. L. (2015). The median split: Robust, refined, and revived. *Social Science Research Network Electronic Journal.* https://doi.org/10.2139/ssrn.2663369

Javed, Z., Maqsood, M. H., Amin, Z., & Nasir, K. (2022). Race and ethnicity and Cardiometabolic risk profile: Disparities across income and health insurance in a national sample of US adults. *Journal of Public Health Management and Practice, 28*(Supplement 1), S91-S100. https://doi.org/10.1097/phh.0000000000001441

Kim, J., Park, S. Y., & Robert, L. P. (2021). Bridging the health disparity of African Americans through conversational agents. *Digital Government: Research and Practice, 2*(1), 1-7. https://doi.org/10.1145/3428122

Kneipp, S. M., & Yarandi, H. N. (2002). Complex sampling designs and statistical issues in secondary analysis. *Western Journal of Nursing Research, 24*(5), 552-566. https://doi.org/10.1177/019394502400446414

Laerd Statistics (2017). Binomial logistic regression using SPSS Statistics. *Statistical tutorials and software guides.* Retrieved from https://statistics.laerd.com/

Latif, K. F. (2021, October 7). *Binary Logistic Regression Analysis using SPSS: What it is, How to Run, and Interpret the Results.* YouTube. https://www.youtube.com/watch?v=tlslGucrD_c

Lederle, M., Tempes, J., & Bitzer, E. M. (2021). Application of Andersen's behavioral model of health services use: a scoping review with a focus on qualitative health services research. *BMJ Open*, *11*(5), e045018. https://doi.org/10.1136/bmjopen-2020-045018

Lin, H. (n.d.). *Effect size converter*. https://www.escal.site/

Lopez-Neyman, S. M., Davis, K., Zohoori, N., Broughton, K., Moore, C., & Miketinas, D. (2022, November 14). *Racial disparities and prevalence of cardiovascular disease risk factors, cardiometabolic risk factors, and cardiovascular health metrics among US adults: NHANES 2011–2018.* Nature. https://www.nature.com/articles/s41598-022-21878-x

MacCallum, R. C., Zhang, S., Preacher, K. J., & Rucker, D. D. (2002). On the practice of dichotomization of quantitative variables. *Psychological Methods*, *7*(1), 19-40. https://doi.org/10.1037/1082-989x.7.1.19

Mercer, A., Lau, A., & Kennedy, C. (2018, January 26). *How different weighting methods work.* Pew Research Center Methods. https://www.pewresearch.org/methods/2018/01/26/how-different-weighting-methods-work/

Moriarity, C., Van, P., Kimball, J., Schar, B., Bose, J., & Bramlett, M. (2022). *Sample Design and Estimation Structures for The National Health Interview Survey, 2016–2025*. https://doi.org/10.15620/cdc:115394

Mugizi, Wilson. (2019). Constructing a Conceptual Framework for Quantitative Data Analysis in Social Science Research. *Interdisciplinary Journal of Education (IJE*). 2. 75-88. https://doi.org/10.53449/ije.v2i1.77

Murphy, S.L., Xu, J.Q., Kochanek, K.D., & Arias, E. (2018). *Mortality in the United States, 2017.* Retrieved from https://www.cdc.gov/nchs/data/databriefs/db328-h.pdf

National Center for Health Statistics (NCHS). (2021, September 31). *NHIS - What is different about the 2020 NHIS data?* Centers for Disease Control and Prevention. https://www.cdc.gov/nchs/nhis/2020nhisdata.htm

National Center for Health Statistics (NCHS). (2021). *NHIS 2020 Dataset Adult Codebook.* https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Dataset_Documentation/NHIS/2020/adult-codebook.pdf

National Center for Health Statistics (NCHS). (2022, September 2). *National Health Interview Survey - 2020.* Centers for Disease Control and Prevention. https://www.cdc.gov/nchs/nhis/2020nhis.htm

Nishisato, S. (2007). *Multidimensional nonlinear descriptive analysis.* Boca Raton, FL: Chapman & Hall/CRC.

Ndugga, N., & Artiga, S. (2021, May 11). *Disparities in Health and Health Care: 5 Key Questions and Answers.* Kaiser Family Foundation

(KFF). https://www.kff.org/racial-equity-and-health-policy/issue-brief/disparities-in-health-and-health-care-5-key-question-and-answers/

Office of Disease Prevention and Health Promotion. (n.d.). *Preventive care.* Home of the Office of Disease Prevention and Health Promotion - health.gov. https://health.gov/healthypeople/objectives-and-data/browse-objectives/preventive-care#cit5

Posadzki, P., Pieper, D., Bajpai, R., Makaruk, H., Könsgen, N., Neuhaus, A. L., & Semwal, M. (2020). Exercise/physical activity and health outcomes: An overview of Cochrane systematic reviews. *BMC Public Health, 20*(1). https://doi.org/10.1186/s12889-020-09855-3

Public health core competencies. (2021, July 7). Public Health Degrees. https://www.publichealthdegrees.org/resources/public-health-core-competencies/

Singh, G., & Lee, H. (2021). Marked disparities in life expectancy by education, poverty level, occupation, and housing tenure in the United States, 1997-2014. *International Journal of Maternal and Child Health and AIDS (IJMA), 10*(1), 7-18. https://doi.org/10.21106/ijma.402

Sparks, H. (2020). Privilege. *International Encyclopedia of Human Geography, Second Edition*, 25-28. https://doi.org/10.1016/b978-0-08-102295-5.10308-7

Tong, S. T., Webel, B. K., Donahue, E. E., Richards, A., Sabo, R. T., Brooks, E. M., Lail Kashiri, P., Huffstetler, A. N., Santana, S., Harris, L. M., & Krist, A. H. (2021). Understanding the Value of the Wellness Visit: A Descriptive Study. *American* *journal of preventive medicine*, *61*(4), 591–595. https://doi.org/10.1016/j.amepre.2021.02.023

Turner, A. (2018, April 24). *The Business Case for Racial Equity: A Strategy for Growth.* Altarum. https://altarum.org/RacialEquity2018

Turner, B. E., Steinberg, J. R., Weeks, B. T., Rodriguez, F., & Cullen, M. R. (2022). Race/ethnicity reporting and representation in US clinical trials: A cohort study. *The Lancet Regional Health - Americas, 11*, 100252. https://doi.org/10.1016/j.lana.2022.100252

U.S. Census Bureau. (2023, March 31). *National population by characteristics: 2020-2022.* Census.gov. https://www.census.gov/data/tables/time-series/demo/popest/2020s-national-detail.html

U.S. Department of Health and Human Services. (n.d.). *Healthy People 2030- Heart disease and stroke.* https://health.gov/healthypeople/objectives-and-data/browse-objectives/heart-disease-and-stroke

Walden University. July 2019. *Statistical Test: Logistic Regression.* -Narrated by Dr. Htway Zin. [Video]. Youtube. https://www.youtube.com/watch?v=Jx1gnW-w1e8&list=PLNgQgQNniJ27Ymr0Dd1Pw5ZisVewmDCeR&index=3

Walden University. May 2021. *Visual Displays of Data.* -Narrated by: Dr. Janine Allwright. [Video]. Youtube. https://www.youtube.com/watch?v=ndXNb5RjK70

Wang, X., & Cheng, Z. (2020). Cross-Sectional Studies: Strengths, Weaknesses, and Recommendations. *Chest*, *158*(1S), S65–S71. https://doi.org/10.1016/j.chest.2020.03.012

Whitfield, G. P., Hyde, E. T., & Carlson, S. A. (2021). Participation in Leisure-Time Aerobic Physical Activity Among Adults, National Health Interview Survey, 1998–2018, *Journal of Physical Activity and Health, 18*(S1), S25-S36. Retrieved Apr 10, 2023, from https://doi.org/10.1123/jpah.2021-0014

World Health Organization (WHO). (2020, December 9). *The top 10 causes of death.* https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death

Yao, Q., Li, X., Luo, F., Yang, L., Liu, C., & Sun, J. (2019). The historical roots and seminal research on health equity: a referenced publication year spectroscopy (RPYS) analysis. *International Journal for Equity in Health, 18*(1), 152. https://doi.org/10.1186/s12939-019-1058-3