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# Factors Influencing Unmet Medical Need among U.S. Adults: Disparities in Access to Health Services

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# FACTORS INFLUENCING UNMET MEDICAL NEED AMONG U.S. ADULTS: DISPARITIES IN ACCESS TO HEALTH SERVICES

by

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# ABSTRACT

Inequities in access to health services has negative consequences on individual well-being, and imposes financial and emotional burden on patients, families, health care systems, and the public. Inequities engendered from differences in socioeconomic status, health insurance coverage, race, and other characteristics can engender disparities. This study aimed to identify the potential predictors of unmet medical need among the civilian noninstitutionalized U.S. adults. Inability to receive needed medical care or receiving medical care after a delay, due to the associated costs, constructed unmet medical need. This study used a four-year (2014-2017) National Health Interview Survey (NHIS) data (sample size: 296,301 adults) and implemented a conceptual framework to study disparities in access to health services and estimate the relative importance of predisposing, enabling, and need factors as the predictors of unmet medical need. Findings from machine learning and logistics regression models highlight the importance of health insurance coverage as a key contributing factor of health disparities. About 60% of variation in unmet medical need was predictable, with over 90% accuracy, solely with health insurance coverage status. Self-rated health status, family structure, and family income to poverty ratio were other statistically significant predictors. Even after controlling for a wide variety of sociodemographic and health status variables such as age, gender, perceived health status, education, income, etc., health insurance remains significantly associated with unmet medical need (OR: 5.03, 95%CI: 4.67-5.42). To ensure precise national estimates, proper survey data analysis methods were incorporated to account for the complex sampling method used by NHIS. Furthermore, the enabling factors (health insurance and income) exert much more weight on unmet medical need than predisposing factors and need factors. The findings raise the concerns about the existence and magnitude of disparities in health care access and provide a comprehensive framework to a target population for understanding the sources of health inequities with data-driven evidence. Results can be utilized to address potential areas for designing public policy and program interventions by identifying the relative vulnerability of different population groups for lacking access to affordable health services. Future studies using longitudinal panel data are necessary to establish a causal relationship between the predictors and unmet medical need.

*Keywords*: health disparities, unmet medical need, the United States, health inequity, health insurance, access to health services

For

Courage, Curiosity, and Skepticism

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# LIST OF ACRONYMS

ACA: Affordable Care Act

AIC: Akaike information criterion

AID: Automatic Interaction Detection

BIC: Bayesian information criterion

CART: Classification and Regression Trees

CDC: Centers for Disease Control and Prevention

CHAID: Chi-square Automatic Interaction Detector

CI: Confidence Interval

NCHS: National Center for Health Statistics

NHIS: National Health Interview Survey

OLS: Ordinary Least Squared

OR: Odds Ratio

P: P Value

U.S. adults: Civilian noninstitutionalized U.S. adults

# CHAPTER ONE: INTRODUCTION

Unmet medical need is an indicator of health disparities or inaccessibility of needed health services. It can lead to more complications in personal health and cause an increase in future emotional and financial burden to individuals, families, health care systems, and the public. This introduction begins by addressing why health and health care services deserve public attention. Then, to highlight the importance of the issue, unmet health care need and the future consequences of it are discussed. Then, the differences between perceived and objective health needs and importance of perceived (subjective) need are discussed. This chapter ends with addressing the gaps in previous studies and highlighting the need for developing a systematic and thorough research on factors influencing health disparities.

## Background

### Health as a Public Concern

Health, both for individuals and the public, can be viewed as a precious commodity. From an individual standpoint, a healthier person, both in terms of pleasure and work, can enjoy more and better choices in life than a person with poorer health. The concomitants of better health and financial affluence are often viewed at both individual and public levels. However, as shown in Figure 1, a vicious circle of disease, disability and poverty engenders the gap between the poor unhealthy and the rich healthy populations (Trani & Loeb, 2012). This gap contributes to overall disparities and inequities in all aspects of life, such as access to necessities, education, employment, and other opportunities.

Because documented substantial differences exist between the haves and have-nots in health and access to health care services (Aber, Jones, & Cohen, 2000; Wagstaff, 2002), urgent and essential research for addressing the causes and consequences of health disparities calls for thorough investigation, particularly in the field of population health (Frohlich & Potvin, 2008). To a certain extent, health and most of the health care services are considered to fall under public good domain (L. C. Chen, Evans, & Cash, 1999). In other words, the concerns and issues related to the health and well-being of people cannot, and should not, be left to be manipulated and regulated solely by the market mechanisms (Sandel, 2012).

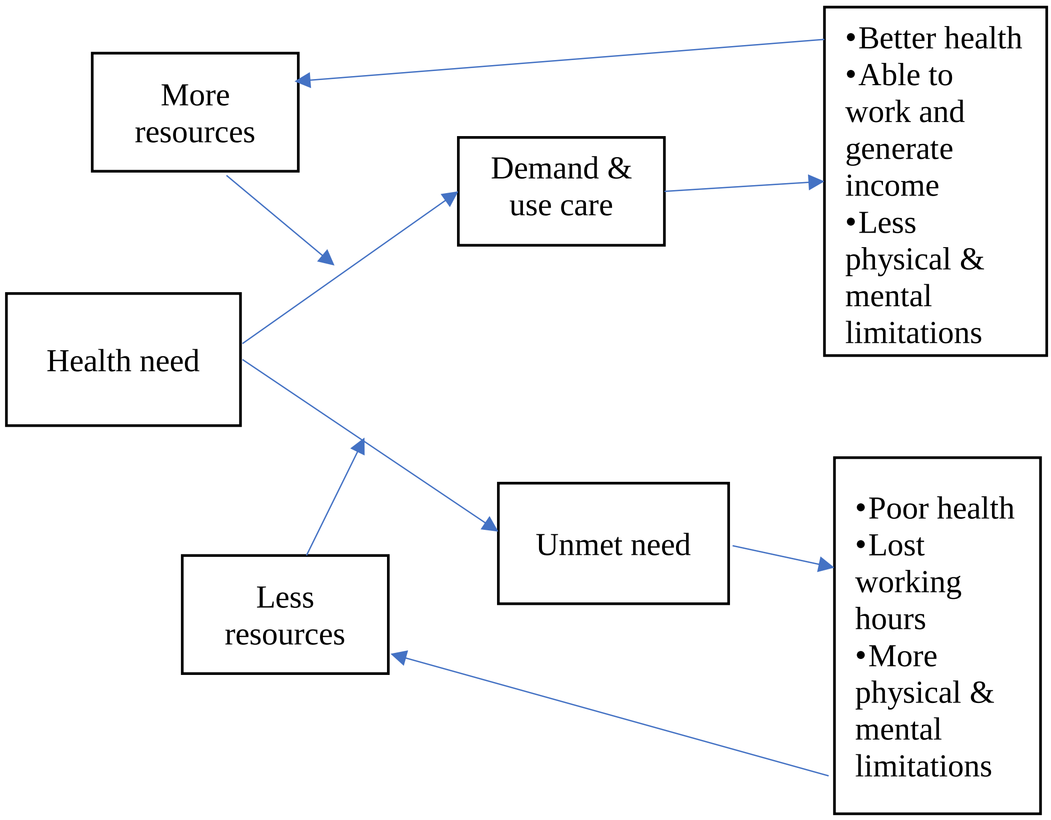


*Figure 1. Understanding the vicious circle of unmet health need and health status*

The extent of government involvement in production, delivery, regulation, and distribution of resources for health and health care services varies widely between different countries depending on the developmental context, the political system, and the approach towards population health. Among the developed nations, many European countries and Canada have adopted a universal health insurance system (Schoenborn, Adams, & Peregoy, 2013). In most of the developed countries, primary and necessary health care services are provided or financed by the public sector, and other more elective and luxury services—such as elective surgeries or plastic surgeries—are provided or financed by the private sector (Rothgang et al., 2010).

In the United States, there are several public health insurance plans, such as Medicare and Medicaid, which are funded by federal or state governments to increase the vulnerable population's access to basic health services (Rice et al., 2013). In 2010, the Affordable Care Act (ACA) was enacted to help the U.S. population receive affordable health services (Sommers, Buchmueller, Decker, Carey, & Kronick, 2012). Despite the efforts of forming accountable care organizations, there is still a considerable number of individuals experiencing serious unmet health needs. The principal reasons for the unmet health needs can be differentiated by the type of health care system and nature of the health care need. For example, in the majority of countries with universal health insurance coverage or public provision of health services, the dominant reason for unmet health need can be attributed to long waiting lists or preference over the specific providers. However, in the United States the most common reason appears to be related to the direct cost and indirect expenses associated with receiving health services, especially unaffordable out-of-pocket payments (Ayanian, Weissman, Schneider, Ginsburg, & Zaslavsky, 2000; Hou & Chen, 2002).

## The Significance of Unmet Health Need

Limitations and restrictions in access to timely, effective, and efficient care may have negative consequences on individuals and the public for several possible reasons. Unavailability and inaccessibility of affordable health care services for prevention, diagnosis, prognosis, treatment, and rehabilitation of current health and medical conditions can lead to future complications and substantial burden to the individual, family, health care system, and public (Friedman & Basu, 2004). For example, postponing a necessary routine visit to a primary care physician because of inability to pay for the out-of-pocket cost can exacerbate the existing condition and worsen the person’s Quality Adjusted Life Years (QALYs). Consequently, it can lead to frequent emergency room visits and use of complex medical services involving more personnel, time, capital, and sophisticated health technologies. More costs are associated with emergency room visits and medical care of the services once the existing health issue is complicated and advanced. Given the scarcity of resources in health care systems, unmet medical need can be tolerated to a certain extent. However, when these unmet needs become more severe and prevalent in all socioeconomic strata of the population (Allin, Grignon, & Le Grand, 2010), it deserves more careful attention to systematically investigate all sources of health disparities attributable to unmet medical need, irrespective of socioeconomic or demographic groups.

According to estimations from the National Health Interview Survey (NHIS), more than 10% of the U.S. population (civilian noninstitutionalized) reported to experience unmet medical need in 2016 (CDC, 2017). According to the results of a 2004 Commonwealth Fund survey, more than half of the lower income respondents in the United States did not receive health care services because of the cost of care. Additionally, 9% of the U.S. respondents had no access to a doctor or a usual place for care (Blackwell, Martinez, Gentleman, Sanmartin, & Berthelot, 2009).

## Objective and Perceived Unmet Health Need

Unmet medical need can be measured in both objective (clinical) and subjective (perceived) ways (Carr & Wolfe, 1976). The objective way of determining medical need, and similarly unmet medical need, can be a medical examination or a health professional assessment accompanied by screening, lab-results, and diagnostic tests. On the other hand, the subjective medical need can be measured by asking if a given person thinks he or she needs to receive any medical care or has experienced unmet medical need (Middelboe et al., 2001).

Initially, it might seem that objective assessments of medical need might offer more valid and predictable service utilization than subjective (perceived) need for care. However, the perceived and self-assessed medical need is a more important factor in influencing personal decisions in regards to utilization of different types and volume (quantity) of medical services (R. M. Andersen, 1995). In other words, any given person's demand for medical care is most likely to be affected by personal judgment (perception) than actual need estimated based on the previous and current medical conditions and health profiles. Asymmetric information between individuals and health care providers and suppliers about health needs is another reason for the importance of the subjective need for medical care. That is, physicians and other care givers depend on the information provided by the individual patient to decide in the diagnosis and treatment. In most cases, except for emergency and obvious life-threatening situations, the perception and preferences of an individual directs the health care seeking behavior (Allin et al., 2010). As a result, perceived unmet medical need, or health need in general, deserves considerable attention from policymakers and those who are concerned with the equity, stable growth, and prosperity of the nation.

## The Significance and Purpose of this Study

Because of the importance of unmet medical need and existing gaps in the literature, this study aims to contribute to new knowledge and policy for eradicating or reducing health disparities. Previous studies cited a variety of unmet medical need of patients with specific medical conditions, such as mental health issues (Garland et al., 2005) or patients with panic disorder (Craske et al., 2005), specific groups such as children (G. Flores, M. Abreu, M. Olivar, & B. Kastner, 1998), in small settings such as hospitals (Weisman, Stern, Fielding, & Epstein, 1991), specific geographic areas such as rural residence (A. C. Skinner, R. T. Slifkin, & M. L. Mayer, 2006), and with limited sociodemographic or clinical predictors. Additionally, access and utilization of a single or limited number of services (Flores & Tomany-Korman, 2008; Lasser, Himmelstein, & Woolhandler, 2006), such as physician visits (Blackwell et al., 2009) were analyzed by several studies. There is a pressing need for a thorough investigation, using multiple years of data from a nationally representative sample that includes more explanatory variables, to understand perceived unmet medical need and its determinants among U.S. adults. Moreover, more is needed to be known about the relative importance of the predictors and identification of the high-risk populations on a population level.

This study investigated the association of a wide range of factors with perceived unmet medical need. Similar to the behavioral system model of health services utilization that was first introduced by Ronald Andersen (1968), predictors were grouped into predisposing, enabling, and need-for-care. Four years (2014-2017) of National Health Interview Survey (NHIS) data were analyzed by considering complex sample design to estimate nationally generalizable findings. NHIS is conducted by the Centers for Disease Control and Prevention.

The larger sample size, multiple recent years, and inclusion of more variables can provide a holistic nationwide view about the prevalence of perceived unmet medical need and helps policymakers identify groups with higher risk of negative consequences of health disparities. The pooled cross-sectional data with multiple years can provide a potential explanation for the overall impact of major national health policies, specifically in relation to the Affordable Care Act (ACA), during the four-year period (2014-2017).

Besides the logistic regression models, Classification and Regression Tree (CART) and Chi-square Automatic Interaction Detection (CHAID) from Machine Learning (ML) are implemented to estimate the relative importance of the variables in association with unmet medical need. Outputs from CART and other machine learning techniques are used to identify and categorize high-risk and vulnerable populations, who, disproportionately, are more likely to experience unmet medical need. Results from these models provide a guidance to rank the high-risk population based on the interactions among the different predictor variables. The classification of vulnerable populations helps policy makers in designing and implementing evidence-based policies and programs that are beneficial, specifically to high-risk population groups. Inclusion of more mutable variables, such as income and health insurance, in the analysis enables us to identify specific public policies and interventions that are likely to influence the reduction or elimination of health disparities.

# CHAPTER TWO: LITERATURE REVIEW

This chapter begins by explaining different economic and behavioral concepts required for actualization of need. Then, to highlight the importance of health as a public concern, several differences between the health services market with the classic free market are addressed. Next, a wide variety of factors influencing health status are discussed to bring attention to one of the components that influence health status: the use of health services. Afterwards, based on previous studies and the literature on the topic, the dependent variable of the study, unmet medical need, along with the potential influential factors are discussed. This chapter ends by explaining a theoretical model, formulated by integrating the determinants and consequences of disparities attributable to unmet health needs.

## Relevant Literature

### From Need to Utility

According to the consumer behavior theory in economics, humans have unlimited needs and limited resources to meet these needs. Rational consumers are aiming to maximize the utility with demanding a combination of multiple commodities or services that they can afford considering the budget constraint. A final goal of a consumer is gaining utility, or satisfaction, from consuming any type of commodity or service (Salvatore, 1991).


*Figure 2. The sequence from Need to Utility*

For a potential need to be met in the form of utility (satisfaction) gained from consuming a good or service, multiple factors are involved (Figure 2). Any disruption between any of these stages can lead to unmet or partially met needs.

Need originates from humans' deprivations. Humans have different types of needs such as need for security, shelter, better health, food, sleep, etc. (Doyal & Gough, 1991) that may vary depending on the amalgamation of personal, environmental, cultural, and other contexts and characteristics. At a given time, individuals might be aware or unaware of their needs. Need can be measured in both objective and subjective ways. In an objective identification and assessment of need, different characteristics of the individual, environment, society, and similar factors that are expected to affect one's needs are considered and weighted to estimate the need.

On the other hand, in the subjective approach, one identifies or self-assesses the need for a good or service based on personal judgment that is resulted from accumulated knowledge and attitudes. A need can transfer to the next phase and become a want if the person identifies it and feels it necessary to seek goods or services to fulfill the need.

Demand is impacted by scarcity of resources and budget constraint of a consumer. That is, even if a person identifies and feels the need for a specific commodity or service, still one needs to make sure about both the availability of that commodity or service (supply side) and ability of the consumer to pay for the given good or service and purchase it. It can be said that a want can form a demand if only it is backed up with an ability to afford and pay for the commodity or service. Different factors are expected to influence an individual's demand for a specific type and quantity of a good or service. The price of the good or service, the price of the other goods or services that can be substituted or are complementary to the current demand, the expectations of the consumer about future prices and needs, along with the expected satisfaction from consumption, affect the decision for current and future choices (Salvatore, 1991).

After forming a demand for a good or service, one can expect to gain satisfaction, happiness, or utility by consuming that good or service. The final step is measured through a subjective term of utility that usually is defined as the satisfaction that a person gains from consuming a good or receiving a service or care (Salvatore, 1991). Using a wide range of variables, this study investigates the inability to move from the steps of need and want towards the next steps of demand and utilization.

## The Case of Medical Care

Market theory assumes that consumers have complete information about the quality, alternative choices, and consequences of consuming a good or receiving a service. This theory is known as "consumer sovereignty" (Penz, 2008). It indicates that consumers can best determine what type and at what quantities different goods and services should be produced in the society, and producers and service delivery organizations only supply what the consumers want. However, most of the health care markets vary from a conventional economic market in several ways that affect, in one way or another, the sequence from need to utility (satisfaction).

### Existence of the Externalities in Health Care Markets

The classic theory of consumer behavior assumes that the final utility or satisfaction gained from a good or service only affects those who are the consumers. That is, satisfaction or dissatisfaction from utilizing a given good or service is limited only to those who have paid and consumed it (Frank & Parker, 1991). However, in some cases, the impact of receiving a health service by a person is not exclusive only to that person. For example, if one chooses to receive a vaccination for a communicable disease, not only does the person becomes immune from a specific pathogen, but also it decreases the chances of other unvaccinated individuals to be infected with the same pathogen. Likewise, an individual's unhealthy or life-threatening behavior, such as smoking in public or carelessly spreading a communicable disease, can negatively affect others. This concept is known as externality (Folland, Goodman, & Stano, 2004).

Information Asymmetry:

The consumer behavior model assumes that a given consumer has a complete knowledge of the demanded good or service along with the other complementary or substitutive goods and services that one could have demanded (Salvatore, 1991). It further assumes that a consumer understands and properly measures and values the opportunity cost of demanding a specific good or service or combination of goods and services over the other possible alternatives (opportunity cost). Although these assumptions barely hold true to full extent in any given market, it is even less likely to be met in health and medical care arenas because of the inadequate information available to identify alternative ways of meeting one's need or pros and cons of a given care, service, medication, or provider. Additionally, according to the concept of agency relationship, especially in the complex cases of medical care, patients delegate their choices in demanding a specific care to physicians or other health care providers (Folland et al., 2004). This lack of complete knowledge and existence of asymmetric information between different parties can affect a person's perception of need.

These concerns, along with other instances of market failure in health care markets (Folland et al., 2004), highlight that health and medical care should be, at least to some extent, treated as a public policy concern and not be left to be directed and controlled solely by the invisible hands of market.

## Social Determinants of Health

Different factors affect and determine the health status and well-being of individuals and communities. These factors may have additive or synergic effects on health status (WHO, n.d.). As shown in *Figure* 3, these predictive factors can be categorized into five main groups with some factors resulting from individual choices and characteristics and some other beyond the immediate control of the person: public policies, social and environmental factors, individual characteristics, health behaviors, and health services utilization.

Public policies and the importance that policy makers and the political system give to health and health care services can affect the health status of most individuals. Additionally, the characteristics of the environment and community that a person is living in can affect the health of the person.

Some other dimensions are more related to the individual characteristics of the person (such as age, gender, and history of illness) and sometimes within the control of the person (such as health behavior, physical activity, or life style).

The last dimension that is believed to affect the health status is access to and utilization of health and medical care services. Like the other categories affecting the health status, any unmet or delayed medical need can have negative impact on the health status of the individuals. Therefore, any unmet medical need can have substantial financial and health burden on the individual, family, health care system, and public.

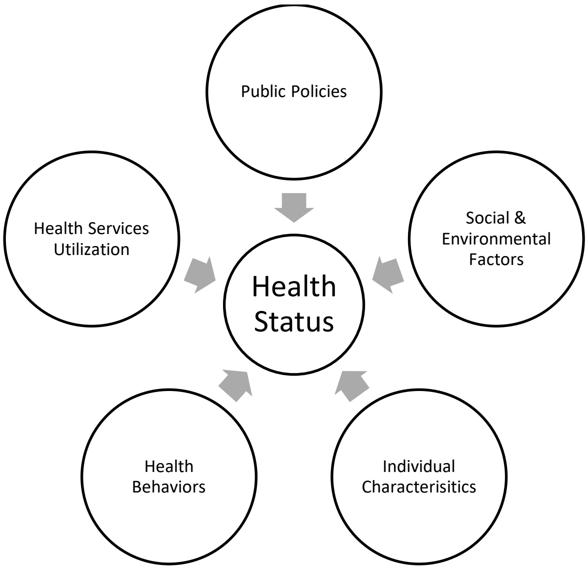


*Figure 3. Social and Individual Determinants of Health*

## Unmet Medical Need

Need for care is a very vague concept to conceptualize and measure (Allin et al., 2010). A proper definition of need for medical care, and therefore unmet medical need, requires considering multiple factors such as physiological characteristics, health and medication history, available public and individual resources, etc. The notion of medical care is generally defined as health services that are necessary to prevent, diagnose, or cure a disease or recover pre-disease health status (Dicker, Ford, & Williams, 2016). Usually, for the matter of the research and comparability, two main approaches are adopted to measure and estimate need for care and unmet need. In the first approach, researchers estimate and compare need for care by identifying the factors affecting a specific class of health needs. For example, the history of health services utilization measured through self-statement or medical records can be used as a proxy for need for care. The second approach is a subjective self-assessed need for medical care that is solely based on the individual perception of need for medical care. Perceived unmet medical need is usually measured in national surveys through self-stated unmet or delayed medical need. Several previous studies implemented perceived unmet need as a dependent variable (for example, Craske et al., 2005).

From a patient's point of view, the price and income elasticity (Folland et al., 2004) of a given medical care is one of the main, if not the main, determinant factors in the potential of experiencing an unmet medical need. That is, life threatening and necessary health care services (such as emergency room visits) are less likely to be delayed or left unmet than health care needs with less devastating effects on health (mostly chronic conditions).

Unmet medical need is studied in different groups of patients and conditions like mental health need among children (Kataoka, Zhang, & Wells, 2002), patients with panic disorder (Craske et al., 2005), children with Autism Spectrum Disorder (Chiri & Warfield, 2012) or other special health care needs (Mayer, Skinner, Slifkin, & National Survey of Children With Special Health Care, 2004; Newacheck, Hughes, Hung, Wong, & Stoddard, 2000; Warfield & Gulley, 2006), unmet need for mental health care (Anderson & Gittler, 2005; Ojeda & Bergstresser, 2008; Roll, Kennedy, Tran, & Howell, 2013; Wells, Klap, Koike, & Sherbourne, 2001), children with vision (Heslin, Casey, Shaheen, Cardenas, & Baker, 2006) or dental (Asheley Cockrell Skinner, Rebecca T Slifkin, & Michelle L Mayer, 2006) care needs, and people with disabilities (McColl, Jarzynowska, & Shortt, 2010).

Some studies focused on the broader concept of health needs (Allin et al., 2010; Bryant, Leaver, & Dunn, 2009; Zheng Wu, Margaret J Penning, & Christoph M Schimmele, 2005), while others focused on only medical needs(Tucker-Seeley, Mitchell, Shires, & Modlin, 2015). Several studies only focused on delayed health care need (Prentice & Pizer, 2007; Weissman, Stern, Fielding, & Epstein, 1991), while others studied a combination of delayed and unmet need (Mollborn, Stepanikova, & Cook, 2005).

## Potential Factors Affecting Unmet Medical Need

Unmet medical need can be studied with analogies to the need for health care services and utilization of health care services. That is, since unmet medical need is believed to result from need for medical care or medication, similar deductions can be made using the variables that usually are implemented as the predictors of potential need. The most commonly used variables and predictors are grouped under different categories and presented here.

### Sociodemographic Factors

The first group of variables frequently used in multiple studies can be grouped under the sociodemographic (Bryant et al., 2009) predictors of the potential medical need or utilization of the services. Among these factors are the personal, familial, household, and ethnical characteristics such as gender, age, race (Bryant et al., 2009; Diamant et al., 2004; Kataoka et al., 2002; Ojeda & Bergstresser, 2008; Roll et al., 2013; Zheng Wu et al., 2005), education and income (Craske et al., 2005; Diamant et al., 2004; Flores, Bauchner, Feinstein, & Nguyen, 1999; Kataoka et al., 2002; Morris, Sutton, & Gravelle, 2005; Ojeda & Bergstresser, 2008; Roll et al., 2013; Zheng Wu et al., 2005), employment (Ojeda & Bergstresser, 2008), race-ethnicity (E. Chen, Martin, & Matthews, 2006; Diamant et al., 2004; G. Flores, M. Abreu, M. A. Olivar, & B. Kastner, 1998; Garland et al., 2005; Heslin et al., 2006; Kataoka et al., 2002; Morris et al., 2005; Ojeda & Bergstresser, 2008; Weissman et al., 1991), nativity (Ojeda & Bergstresser, 2008; Warfield & Gulley, 2006), immigrant status (Zheng Wu et al., 2005), rurality of the residential area (Anderson & Gittler, 2005), marital status (Roll et al., 2013; Tucker-Seeley et al., 2015; Zheng Wu et al., 2005), and language fluency barriers (Documét & Sharma, 2004), which were implemented to highlight the existence, and in some cases, magnitude of disparities in access to and utilization of health services or unmet health need.

Age and Gender

Among other studies, in a study by Kataoka et al. (2002), children 12 to 17 years old were less likely to experience unmet mental care need than their counterparts in the 6-11 age group. In another study (Roll et al., 2013) seniors (65 years or older) were less likely to experience unmet mental health need than both children (under 18 years old) and working-age adults (18-64 years old). Contrary to this finding, in a Canadian study (Bryant et al., 2009) persons less than 55 years old were less likely to experience unmet health need than persons aged 55 years or more.

Like these results on age, there were inconsistencies in findings for almost all the variables. A review of literature in public health, epidemiology, health economics and other related fields provides justifications for using these variables in studies of health care services utilization, access, need assessment, and relevant studies. In general, females tend to have less health-related risky behaviors and take more care of their health than their male counterparts (Kandrack, Grant, & Segall, 1991; Ridley, 1993). This can be observed in the differences in men's and women's life expectancies internationally. Women's life expectancy at birth is higher than men's in all countries (Barford, Dorling, Smith, & Shaw, 2006). However, some studies show that women are more likely to experience unmet health care need (Bryant et al., 2009).

In general, elderly (more dependent family members) have more health care needs than children at school ages and adults at productive ages (Neugarten, 1974). As a result, it is expected to see, holding other factors constant, higher chances of delayed or denied medical care among the oldest adults than younger-adults.

### Education and Income

Education and income might have, theoretically, two opposite effects on the perceived need for medical care. Increased income and higher level of education can promote a healthy lifestyle (Adamson, Ben-Shlomo, Chaturvedi, & Donovan, 2003) and, consequently, decrease need for medical care. On the other hand, however, a higher level of income provides more purchasing power for buying and utilizing less necessary and luxury health services. Similarly, higher educational attainment helps people to understand and identify more medical needs and demand more services. Higher income improves the quality of life and decreases the need for medical care due to chronic conditions and disabilities. Contrary to most of the studies, in some studies, it was found that the chance of unmet health care need is more in people with lower income (Bryant et al., 2009) and lower educational attainment (E. Chen et al., 2006).

Parental education can contribute to better health status of family members through direct and indirect ways (Cochrane, OHara, & Leslie, 1980). Education can help individuals in understanding and distinguishing the health care needs of family members. On the other hand, educated parents are more likely to be successful in making informed decisions in choosing the type of health care needed and proper health care giver. Parental education can indirectly affect the health status and need for health care through changes in the overall family income. That is, family members with higher levels of education are more likely to earn more money. Higher income can help a family with more financial access to needed health care through paying for a health insurance premium with better coverage or ability to pay out of pocket cost of services. Higher education and, consequently, higher income is expected to promote the quality of life through better lifestyle and nutrition and decreases the need for health care (Atkinson & Bourguignon, 2014).

### Family structure

The presence of parents in family, especially in younger ages can provide more emotional and financial support in case of a health threatening condition and homecare in sicknesses or chronic disabilities (Palmer, 1993). With divorced or separated parents, one can experience more stress and less support both for adults and children. The absence of one or both of the parents in a family can increase the need for health care and raise the probabilities of experiencing unmet medical need in children.

Family structure can affect one's health status, need for health care and the potential of facing unmet medical need. In general, married people have less health-related risky behaviors and have more access to emotional and care giving support in case of sickness (Lillard & Panis, 1996; Waite, 1995). For example, in one study, although it was not constantly significant in all models, married people were less likely to experience unmet medical need than divorced, separated, single, and never married people (Bryant et al., 2009).

### Race and Ethnicity

Racial and ethnical minorities have been shown to be more likely to be negatively impacted by inequities in access to quality health care. For example, Wolinsky et al. (1989) found that there were less differences between the utilization of less-discretionary services such as hospitalization among Whites and minorities. However, there were significant differences in more-discretionary service utilization such as physician office visits between Whites and minorities (White Americans utilized more than minorities). Studies regarding disparities in access to health services and health indicators, such as infant mortality rate and child care, show lower levels of health status and higher levels of health care needs and unmet health needs (Documét & Sharma, 2004). Place of birth, immigration status, and English language fluency have been used in several studies to highlight disparities in unmet health care needs and access to health care services with inconsistent findings (Documét & Sharma, 2004; Zheng Wu et al., 2005).

Health Insurance Coverage

In most of the studies focused on access to health care services and unmet health needs, health insurance coverage was one of the significant determinants regardless of the specific group and health condition focus of the study. Health insurance was measured in various ways. Some studies coded the insurance coverage as a dichotomous variable of with and without health insurance coverage (Craske et al., 2005; Documét & Sharma, 2004; Flores & Tomany-Korman, 2008; Folland et al., 2004; Garland et al., 2005; Heslin et al., 2006; Newacheck, Hung, Jane Park, Brindis, & Irwin, 2003; Roll et al., 2013; Tucker-Seeley et al., 2015; Wells et al., 2001), public or private coverages (Kataoka et al., 2002; Newacheck et al., 2000; Roll et al., 2013), specific type of insurance coverage such as Medicare, Medicaid, Blue Cross, Health Maintenance Organizations, etc. (Mayer et al., 2004; Newacheck et al., 2000; A. C. Skinner et al., 2006; Warfield & Gulley, 2006; Weissman et al., 1991), and existence and length of the gap in insurance coverage (Mayer et al., 2004; Newacheck et al., 2000; Warfield & Gulley, 2006).

Health insurance facilitates access to health care and services through increasing financial access by, in turn, decreasing out-of-pocket payments for services (McPake, Normand, & Smith, 2013). Uninsured or people with a gap in health insurance coverage are more likely to lack access to health care services and experience unmet medical need. Aside from business or employer-based health insurances, the U.S. health system offers several federal and state funded or assisted insurance plans for the elderly or people with specific health conditions. Medicare, Medicaid, and Children's Health Insurance Program (CHIP) are among the health insurance coverage plans for increasing access to health services and decreasing health inequity in the United States (Newacheck et al., 2003; Rice et al., 2013).

## Perceived Health Status

Current health status has been used as a predictor for health care utilization, estimation of the need for medical care, and chances of experiencing unmet medical need. Health status is usually measured by self-assessed health status and well-being on a Likert scale, ranging from excellent to poor health. Poorer health status was associated with higher perceived need for medical care and higher chances of experiencing unmet medical need (Bryant et al., 2009; Flores et al., 1999; Morris et al., 2005; Newacheck et al., 2000; Newacheck et al., 2003; Warfield & Gulley, 2006; Zheng Wu et al., 2005).

## Physical or Mental Limitations

Existence of one or more limitations in performing activities of daily living have been shown to be a significant predictor of experiencing unmet medical need. Activity limitations in the previous week usually was used as a binary dummy variable for having any limitations in activity (Anderson & Gittler, 2005; Newacheck et al., 2000; Newacheck et al., 2003; Roll et al., 2013) or an ordinal scale of functional ability (Chiri & Warfield, 2012). Studies on specific health conditions, such as children with special health care needs (Heslin et al., 2006; A. C. Skinner et al., 2006; Warfield & Gulley, 2006) and mortality (Lo & Fulda, 2008), found that coexistence (Morris et al., 2005; Zheng Wu et al., 2005) and severity (A. C. Skinner et al., 2006) of mental health issues (Anderson & Gittler, 2005; Craske et al., 2005; Ojeda & Bergstresser, 2008; Wells et al., 2001), substance abuse (Wells et al., 2001), stress (Bryant et al., 2009; Zheng Wu et al., 2005), cancer, heart disease, and neurological disease (Prentice & Pizer, 2007) increased the risk of experiencing unmet medical need.

Prior Utilization of Health Care Services

In several studies, past consumption of health and medical care was found to be a significant predictor of unmet medical need and access to and utilization of health care services. For example, history of hospitalization measured by the number of overnight hospitalization (Flores et al., 1999; Newacheck et al., 2000) and the frequency of past physician visits (Mollborn et al., 2005) are used frequently in the literature.

Need for health care can be measured and estimated in different ways. Clinical examinations, diagnostic tests, and screenings are the most accurate and comprehensive methods for measuring actual need for care. However, these approaches are highly expensive and time consuming for collecting data of a nationally representative sample of population. Some other proxies such as perceived health status, physical or psychological limitations in performing daily tasks, and current use of health care (e.g. office visits and hospitalization records) can predict future need for health care. In general, those with higher need for health care are expected to experience more unmet medical need. This can be seen indirectly through decreasing productive power and ability to earn money (income), and consequently, ability to buy health insurance, pay for necessary health care services as well as other necessities.

A few studies compared the relative influence of the different variables on utilization of health services and unmet medical need (Miranda-Castillo et al., 2010; Stein, Andersen, & Gelberg, 2007; Wolinsky & Johnson, 1991) . In some cases, presence of medical conditions, poor health status, and other need factors were shown to be more determinant in the utilization of health care services and experiencing unmet medical needs than other factors such as sociodemographic factors, income, and health insurance.

## Conclusion

There are inconsistencies in the literature on the significance and direction of the influence of the several predictor variables on the outcome variable of health services utilization or unmet health needs. The factors such as differences in study population and sample, study design, sampling, analysis methods, study setting, country, and other factors can explain the variations in findings.

Though the literature on health services utilization is abundant, there are limited studies addressing unmet medical need. Previous studies identified the need factors such as presence of physical or mental conditions as dominant predictors of health services utilization. However, considering experiencing unmet medical need as the dependent variable, enabling factors might be more influential than the need factors. This study aimed to extend the existing literature by comparing the relative predictive influence of the different variables on unmet medical need.

Moreover, there is a lack of literature on the joint influence of a comprehensive set of different predictors. By including four years of pooled data, incorporating survey data analysis techniques, and statistically controlling for the majority of the relevant variables, this study aimed to estimate the overall impact of the U.S. health policies on unmet medical need and provided four-year national trends on several health-related indicators such as insurance coverage and unmet medical need. Additionally, most of the previous studies used only conventional regression models to study the effects of predictors, holding other variables constant. By using logistic regression and two analytical techniques from machine learning, this study aimed to identify the population groups with higher risks of undergoing unmet medical need.

## Theoretical Framework

### Andersen's Behavioral System Model of Access to Medical Care

The behavioral system model was initially developed by Ronald Andersen (1968) to facilitate and conceptualize understanding of why families utilize health services. This model was a family-level analysis of factors resulting in the use of health services and was a one-way flow of influencing factors from predisposing characteristics (three subcategories of demographic, social structure, and health beliefs variables) to enabling resources (two subcategories of personal/family and community resources). These predisposing and enabling factors determine the health care need, which can be measured in perceived (subjective) and evaluated (objective) ways. The final component of the model was use of health services derived from perceived and evaluated need for care.

Genetic factors (True et al., 1997) and psychological characters such as mental dysfunction and cognitive impairment (Bass, Looman, & Ehrlich, 1992; Rivnyak, Wan, Stegall, Jacobs, & Li, 1989) were later recommended by other researchers to be included among the predisposing characteristics.

Among the enabling resources, community resources measured by availability and accessibility of health care facilities, providers, and personnel are prerequisites for personal and family related enabling factors such as income and health insurance to contribute to health care services utilization.

Empirical studies have shown that the need factors are the main determinants of demand and utilization of health services (Wolinsky & Johnson, 1991). The perceived need is a social phenomenon that can be explained by social structure and health beliefs (R. M. Andersen, 1995).

Depending on the services, different factors in the model can have different impacts on utilization of health services. For example, more serious health problems and emergency room visits can be explained more by need factors. However, dental services or cosmetic plastic surgery can be explained more by social structure, beliefs, and enabling factors.

Andersen and Newman (1973) discussed the concept of mutability of determinant factors of health services utilization. Mutability is defined as the potential for change by public policies especially in the short-term. This notion is important in addressing public tools and interventions in targeting equitable access to health services. If a given factor that is expected to affect health services utilization is more prone to be changed, it should be considered as a potential impact point of public policies. For example, demographic characteristics such as gender and age are considered to have low mutability. On the other hand, for example, health insurance has been shown to be more mutable, therefore more helpful in affecting access to health services (Manning et al., 1987). Comparing pre- and post-intervention variances can be beneficial in studying new interventions or gradual change in the policies.

Figure 4 shows a model that has been adapted from Andersen's first behavioral model. Each group of variables are expected to influence the ability, intention, and behavior of using health services, mainly through direct impact.

The second revision of the model in the 1970s included another component: health care system. In this model, use of health care was determined by population characteristics (predisposing, enabling, and need), health care system (policy, resources, and organization), and interaction between these two components. Then, use of health services variables were expected to impact consumer satisfaction measured by indicators of convenience, availability of services, financing, provider characteristics, and quality. This phase was more focused on individual level outcomes of satisfaction than public health indicators or other health outcomes.

In the third phase of the model, health outcomes (perceived and evaluated health status) along with consumer satisfaction were the final causal component that were expected to be affected by health behaviors, such as personal health practices and use of health services. Health behavior component was driven from primary determinants of health behavior (population characteristics, health care system, and environment)

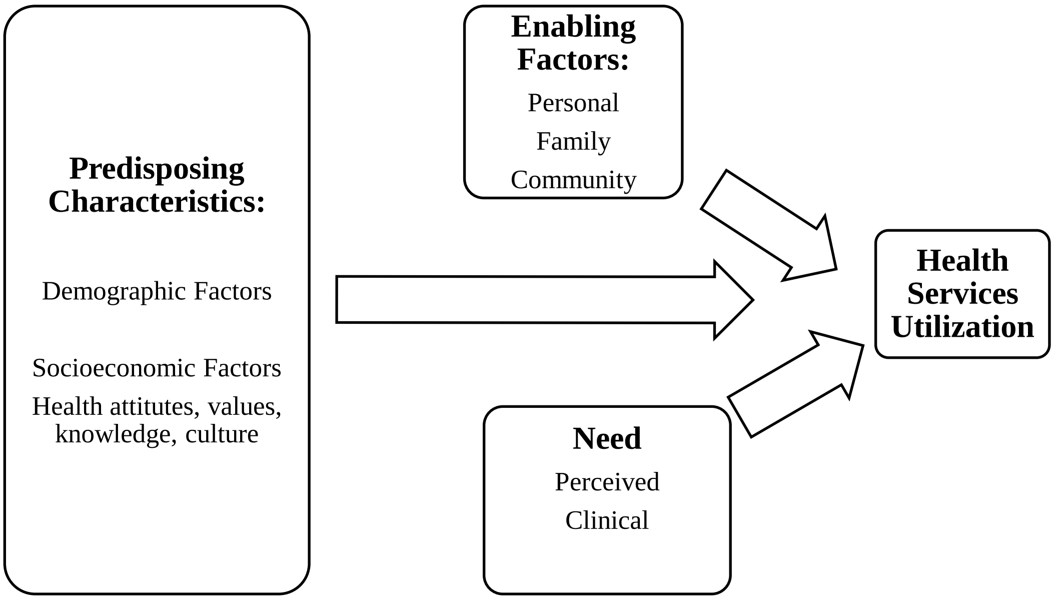


*Figure 4. Predictors of health services utilization. Adapted from Andersen (1995)*

The final phase of the model was introduced by Andersen (1995) indicating the recursive nature of the interaction between various factors in the model. The model consists of four main dimensions of environment, population characteristics, health behavior, and outcomes that, contrary to the previous versions of the model, have recursive causal paths. For example, the health care system and external environment components impact outcomes directly. Environment also impacts outcomes through an indirect path mediated through the impact on population characteristics.

Even though this model needs more precautions and considerations in implementation, analytical results are expected to be more precise because of including a wide range of variables and potential multi-directional recursive impacts (feedback loops) of different elements on each other. All three categories of predisposing, enabling, and need factors influence the use of health services. At the same time, use of health services is expected to be affected by perceived health status.

The comprehensive implementation of this model requires longitudinal, randomized experimental studies. In practice, it is impossible to include all the components of the model along with the recursive relationship among the variables in analysis. This idealistic model, however, depicts the potential variables and directions of causality that can be implemented in more refined studies.

## Application of the Theoretical Approach in Previous Studies

Andersen and his colleagues (2002) applied the behavioral system model of health services utilization to investigate the impact of individual and community-level factors on use of health services for low-income children and adults of large metropolitan statistical areas (MSAs).

Data for the individual-level predisposing, enabling, and need factors were obtained from the 1995 and 1996 National Health Interview Survey (NHIS). Other public data sources were used for community-level variables. Access to health services was measured using a single dichotomous variable of physician visit in the past 12 months.

Individual-level variables were grouped under three domains of predisposing (age, gender, ethnicity, and education), enabling (health insurance, regular source of care, and poverty status), and need (perceived health status). Community-level variables were all defined as the enabling factors and were divided into four different sub-categories of demand (percentage of population below poverty, uninsured, and receiving Medicaid), support (Per capita income, income inequality, and unemployment rate), structure (population ratios of public hospital bed and community health centers), and market dynamics (health maintenance organizations' penetration and competition).

To account for different characteristics and enabling factors between children and adults, different logistic regression models were analyzed separately for children under 19 years old and adults 19 to 64 years old. The first two regression models for children and adults included only predisposing and need variables. In the second stage, individual- and community-level enabling factors were included. The results were interpreted using the odds ratios and the corresponding p-values. According to findings of the study, individuals with health insurance, with a regular source of care, and residing in communities with more federally-funded health centers had better access to health services (measured through last 12-month visit to a physician). In addition, Latino and Asian low-income children and adults and those with lower educational attainment were less likely to visit physicians. Younger age and male adults had less chances of visiting a physician within the last 12 months.

## Conceptual Framework

The first conceptual model of this study, which is presented in Figure 5, classifies predictors of health services utilization similar to Andersen's behavioral system model of health services utilization. This framework is used to understand the factors that are expected to influence the risk of experiencing unmet medical need.

Unmet need is conceptualized in relation to utilization of health services. That is, unmet need results from the felt need for a service or care that has not been received or delayed. In this model, perceived unmet medical need is operationalized by participants' answer of "Yes" to one or both questions (coded as 1, experienced unmet medical need, otherwise 0, did not experience unmet medical need): (1) during the past 12 months, has medical care been delayed for the person because of worry about the cost? (Do not include dental care), and (2) during the past months, was there any time when the person needed medical care, but did not get it because the person couldn't afford it?

Predisposing factors such as age and gender, along with other characteristics such as race-ethnicity, education, family structure, and nativity that have been used in multiple previous studies, are grouped under one category. These variables in Andersen's model were usually labelled as the predisposing and contextual dimensions.

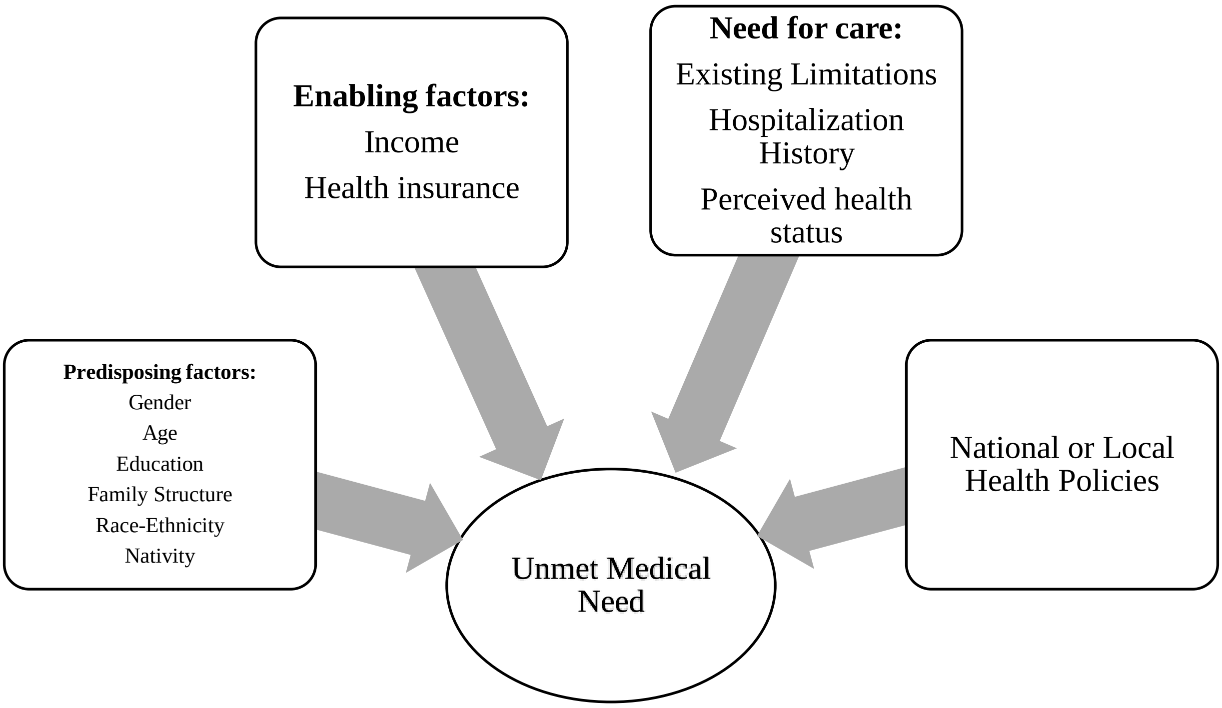


*Figure 5. Conceptual model No.1 to measure the absolute and relative impact of predictors on unmet medical need*

In the conceptual model, several correlations, though probably weak, are expected to be seen between one or multiple components of a dimension or between multiple components from different dimensions. In other words, some variables within a dimension (such as income and health insurance in enabling factors) or between dimensions (such as education and income from predisposing and enabling factors) are shown to impact each other.

The second conceptual model that is shown in Figure 6 focuses on the proportion of unmet medical need to perceived need to address the existence and magnitude of disparities in access to health care and undergoing unmet medical need. That is, in the scenario with optimal equity, it is expected to see equal proportion of unmet medical need compared to the indicators of need.

The ideal scenario is no one should experience unmet medical need. However, because of scarce resources, inefficiency in production, and a range of other factors, one cannot expect the complete eradication of unmet medical need. For simplicity, let's assume person A needs (perceived or evaluated) one doctor visit per month and person B needs to receive the same service every three months. If there are no disparities in access to health services based on the predisposing, enabling, and various factors other than need for service, the equitable proportionate chance of experiencing unmet medical need of person A to B would be 3 to 1. That is, in the case of complete equity, person A and B are expected to experience unmet medical need proportionate to the quantity of their health needs. Any deviation from this optimal proportion represents disparity in access to health services.

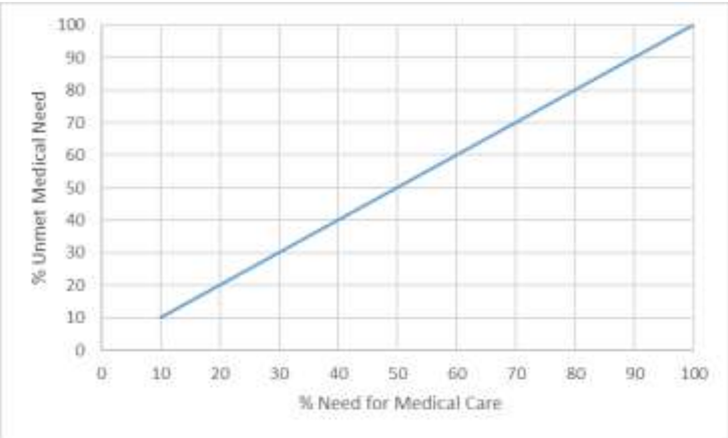


*Figure 6. Conceptual model for proportionate equity in unmet medical need in response to need for care*

The data-driven models using logistic regression, Classification and Regression Trees (CART), and Chi-Square Automatic Interaction Detection (CHAID) address concerns about the disparities in access to health care services. The implementation of these estimation models using empirical data from four years of National Health Interview Survey (NHIS) is beneficial in addressing the relative importance of the variables in predicting unmet medical need. That is, the operationalization of these conceptual models predicted independent variable of perceived unmet medical need, not only by direct effects of the independent variables, but also by identifying the groups of U.S. adults with the highest risk of experiencing unmet medical need.

# CHAPTER THREE: METHODOLOGY

This chapter covers research hypotheses, research design, data source, study population, and sampling. Then, measurements of the study variables, data collection methods, and analytical tools are explained. This chapter ends with data analysis approaches.

## Research Questions and Hypotheses

The dependent variable of interest is perceived unmet medical need. The main objective of this study was to investigate the importance of predictors on experiencing unmet medical need. Since this study used data from four consecutive years, the findings might have some explanatory power in assessing the overall success of national health policies such as ACA. Using previous literature including relevant studies and Andersen's behavioral system model of health services utilization and the conceptual models outlined in the previous chapter, this study aims to test the several research hypotheses with a representative sample of the civilian noninstitutionalized U.S. adult population.

The principal null hypothesis ($H_0$) is defined as the equal chances of experiencing unmet medical need, irrespective of personal and social characteristics. That is, the chances of experiencing perceived unmet medical need cannot, significantly, be attributed to the differences in variables categorized under the three domains of predisposing, enabling, and need factors. Moreover, these three domains of variables attribute to the chances of experiencing unmet medical need to the same extent.

The hypotheses are tested using logistic regression, CART, and CHAID models to answer two main research questions:

Research Question 1: What is the relative importance of the three groups of predisposing, enabling, and healthcare need variables in predicting unmet medical need?

H1A: Enabling factors predict unmet medical need more than predisposing and need factors.

Research Question 2: Which subpopulations of U.S. adults have higher risks of forgoing medical need?

H1B: Groups of population differ significantly in terms of the risk of experiencing unmet medical needs.

Additionally, several following sub-hypotheses are tested:

H1a: Female adults are more likely to have unmet medical need.

H1b: Old adults are more likely to have unmet medical need than middle-aged and young adults.

H1c: Adults with higher educational attainment are less likely to have unmet medical need.

H1d: Compared to their divorced, separated, or single counterparts, married adults are less likely to have unmet medical need.

H1e: Minority ethnic-racial adults are more likely to have unmet medical need than their White counterparts.

H1f: Immigrant adults are more likely to have unmet medical need than those born in the United States.

H1g: Adults with higher family income to Federal Poverty Levels ratios are less likely to experience unmet medical need.

H1h: Adults with no health insurance coverage are more likely to have unmet medical need than those with at least one type of health insurance coverage.

H1i: Adults with at least one mental or physical limitation are more likely to have unmet medical need than those with no limitations.

H1j: Adults with a history of overnight hospitalization in the last 12 months are more likely to experience unmet medical need than those without overnight hospitalization in the last 12 months.

H1k: Poor health status is associated with higher chances of experiencing unmet medical need.

## Research Design

Data from four years (2014-2017) of National Health Interview Survey (NHIS) are used to conduct this pooled cross-sectional study. To better fit the purposes of the study, several variables in the original data are recoded or re-categorized depending on the research questions, univariate distribution, methods of analysis, and other factors.

Logistic regression, CART, and CHAID models are implemented. Perceived unmet need for medical care (Yes/ No) is defined as a dichotomous dependent variable. Independent variables of gender, age, income, education, family structure, race, nativity, health insurance, history of overnight hospitalization, and self-assessed health status are included in the analysis.

Research hypotheses are tested based on the magnitude and significance of the Odds Ratios (ORs) and variance explained by the models using each of the independent variables.

## Population and Sample Selection

NHIS uses a complex sampling method to ensure that the sample is representative of the civilian noninstitutionalized U.S. population. The sample did not include population in long-term health care institutions such as nursing homes or people staying in the hospitals because they are chronically ill or physically or intellectually disabled. Additionally, people in correctional facilities and active-duty Armed Forces are excluded from the survey sample. Active-duty Armed Forces personnel were included in the survey only if one or more of their family members were a civilian eligible for the survey. U.S. nationals living in foreign countries were also excluded from the sample (CDC, 2016).

Sampling and surveying were continued throughout the data year. A multi-stage probability sample design was implemented with the stratification at the state-level. However, according to the NHIS survey description files, the state-level data may not be generalizable for every state (CDC, 2017). Several states contributed financially to NHIS to ensure that collected data is generalizable at the state-level for their state. Otherwise, the sample is generally representative of the United States at the national level. Due to the changes in the sampling design in four years and oversampling of several subpopulations such as Black, Hispanic, and Asian individuals and to prevent from inflated significance findings, a survey design analysis method with different weighting variables are included in the process of data analysis. Simple random sampling of U.S. civilian noninstitutionalized population would be costly and cumbersome and almost, considering the budget limits, impossible to achieve. To address this issue and eliminate the potential biases and other issues inherent to non-randomized sampling approaches, NHIS implements an effective, timely, and less expensive complex sample approach, which included multiple nested strata and clusters.

## Study Variables

Table 1 summarizes the variables of interest in the study. NHIS questionnaire was the measurement tool for all the variables of this study. An informed adult respondent in the family provided answers to all the survey questions related to all family members. Some of the operational definitions are expressed in the question form to show the exact way of measurement.

As a binary (dichotomous) dependent variable, a response of “Yes” to one or both of the following questions is considered as experiencing unmet medical need: (1) during the past 12 months, has medical care been delayed for the person because of worry about the cost? (Do not include dental care), and (2) during the past 12 months, was there any time when the person needed medical care, but did not get it because the person couldn't afford it?

The rest of the variables are grouped in three domains of predisposing, enabling, and need for care factors. The two last variables are the year in which data was collected and geographical region. To provide comparable and explanatory findings, variables are measured or recoded into categories. Age, education, income, and reported health status are ordinal.

Gender, U.S. nativity, existence of any physical or mental limitation, and hospitalization within the last 12 months are dichotomized. The rest of the variables, including family structure, race, health insurance, and year are operationalized and measured by several nominal values without any hierarchical order (not ordinal).

## Data Collection and Measurement

The National Health Interview Survey (NHIS) is a continuing nationwide household survey designed and conducted by the National Center for Health Statistics (NCHS) at Centers for Disease Control and Prevention (CDC) to collect cross-sectional information on the demographic characteristics, health and disability status, and health care utilization of the U.S. civilian noninstitutionalized population (CDC, 2017). NHIS has been recognized as the most comprehensive and updated source of population health data in the United States (Davidoff, 2004).

Measurement and data collection tools are NHIS questionnaires that trained interviewers from NCHS used for collecting data. The majority of variables from NHIS are publicly available. Data were accessed from NHIS and University of Minnesota's Integrated Public Use Microdata Series (IPUMS) (Blewett, Drew, Griffin, King, & Williams, 2018; CDC, 2016, 2017).

According to the NHIS survey description documents, the unconditional or final response rates for the family module questionnaire were 73.1%, 69.3%, 67.1%, and 65.7% for the years 2014, 2015, 2016, and 2017, respectively.

*Table 1. Study variables*

| Variable | Variable Type | Values | Operational Definition |
|---|---|---|---|
| Dependent Variable | | | |
| Perceived Unmet Medical Need | Categorical | Yes<br>No | Has needed medical care been delayed or not received in the last 12 months? |
| Predisposing | | | |
| Gender | Categorical | Male<br>Female | The state of being male or female. |
| Age | Ordinal | Young Adult (18-35)<br>Middle-aged Adult (36-55)<br>Old Adult (55+) | The length of time (in years) that a person has lived. |
| Education | Ordinal | Less than high school<br>High school<br>Some College<br>AA<br>Bachelor's<br>Master's or Higher | Highest level of educational attainment at the time of the interview. |
| Family Structure | Categorical | Married<br>Widowed/Divorced/ Separated<br>Living with partner<br>Never married | State of never married, married, separated, divorced, widowed, or living with the partner. |
| Race / Ethnicity | Categorical | Non-Hispanic White<br>Non-Hispanic Black<br>Hispanic<br>Non-Hispanic Asian<br>Non-Hispanic Other | The self-stated race and ethnicity chosen from multiple options. |
| Citizenship | Categorical | US born & U.S. Citizen<br>Foreign Born & U.S. Citizen<br>Foreign Born & Non-US Citizen | Whether the person was born in the U.S. or another country and current citizenship status. |
| Enabling Factors | | | |
| Ratio of Family Income to Poverty Guidelines | Ordinal | 1.38 and Below<br>1.39 to 2<br>2.01 to 4<br>Above 4 | Self-stated income recoded into the ratio of family income to Federal Poverty Level. |
| Health Insurance | Categorical | NO Coverage<br>Private<br>Medicare<br>Medicaid & other public Coverage<br>Market Exchange | Type(s) of insurance coverage. |
| Need factors | | | |
| Any limitation | Categorical | Not limited in any way<br>Limited in some way | Presence of at least one physical or mental limitation. |
| Has been in a hospital Overnight within 12 months | Categorical | No<br>Yes | Has person been hospitalized overnight in the past 12 months? |
| Reported health status | Ordinal | Excellent<br>Very good<br>Good<br>Fair<br>Poor | Respondent-evaluated health status. |
| Year | Categorical | 2014<br>2015<br>2016 | The calendar year that data was collected. |
| Region | Categorical | Northeast<br>North, Central, and Midwest<br>South<br>West | Geographical region of the U.S. |

## Data Analysis

Data were analyzed using STATA and SPSS Modeler Programs. Univariate statistics such as minimum, maximum, mean, number of observations, and shape of the distribution of data were tested along with the visual presentation of the selected variable to check for potential outliers and quality of the data. Several variables were generated from recoding or merging the original variables.

Complex sampling weighting and design variables were used in the survey data analysis approaches to ensure correct point and variance estimations such as mean, frequency, and standard errors. Additionally, the survey analysis approaches ensure to provide a national estimate of variables in the four years from 2014 to 2017. The U.S. adult population is estimated based on the person weight variable, which is the inverse probability of being selected as the NHIS sample. NHIS data documentation indicates that the sum of the person weight variable in each year is equal to the civilian noninstitutionalized U.S. population in that year (CDC, 2017).

Next, bivariate statistics such as correlation were implemented to study the association and correlation between some of the variables. As a result, several new variables were generated, excluded, or recoded to ensure no multi-collinearity between variables.

The dependent variable of unmet medical need is regressed on the multiple independent variable under three domains of predisposing, enabling, and health care need factors. Additionally, two predictors for study year and geographical region are included in the models. In logistic regression, the covariates (independent variables) should not necessarily be normally distributed or have equal variance in each group. That is, heteroscedasticity is not an issue to be addressed and tested. Since the statistical methods for analyzing data from complex survey designs vary from conventional statistical methods, stratification, clustering, over-sampling, under-sampling, and other relevant weighting variables are included to ensure unbiased generalizable findings.

The resulted regression coefficients are checked for the magnitude, direction, and significance (p-value<.05) of the association with the dependent variable. As alternative and complementary methods of analysis, CART and CHAID models from machine learning are used to estimate the probability of experiencing unmet medical need among various groups of the population with different combinations of values for independent variables. This approach is more beneficial in identifying vulnerable subpopulations considering a set of covariates than a single covariate. For example, it is possible to compare the probability of experiencing unmet medical need between a group of females in the 18-35 years old group without a high school degree with a group of males in the 36-55 years old group with higher education rather than comparing only based on the gender (male or female). Additionally, decision trees provide more interaction terms depending on the different values of the covariates (local interaction) than regression models that only can be customized for the presence of a limited number of interaction terms in the model (global interaction).

## Logistic Regression

The mathematical expression of the logistic regression is explained bellow:

$$\ln\left(\frac{p}{1-p}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon$$

or,

$$\frac{p}{1-p} = e^{\alpha + b_1 X_1 + b_2 X_2 + \cdots + b_n X_n + \varepsilon}$$

Where,

$\frac{p}{1-p}$, Odds Ratio is the probability of the outcome variable happening over the probability of the outcome variable not happening (probability of experiencing unmet medical need over probability of not experiencing unmet medical need).

$b_i$, coefficient is the logit (log-odds) change with one-unit increase in $x_i$ variable.

$\alpha$ is the intercept of the model.

$X_i$, represent the independent variables (covariates such as age, gender etc.) of the model.

Following predictor variables are included in several models in this study:

$X_{1=}$ Gender

$X_{2=}$ Age

$X_{3=}$ Education

$X_{4=}$ Family Structure

$X_{5=}$ Race / Ethnicity

$X_{6=}$ Citizenship

$X_{7=}$ Ratio of Family Income to Poverty Guidelines

$X_{8=}$ Health Insurance

$X_{9=}$ Any physical or mental limitation, all conditions

$X_{10=}$ Has been in a hospital Overnight within 12 months

$X_{11=}$ Reported health status

$X_{12=}$ Data Year

$X_{13=}$ Region

The interpretation of the results from the logistic regression method is not as straightforward as the Ordinary Least Squared (OLS) applied in linear regression method. Fitness of model is measured by the changes in the pseudo R-squared ($R^2$). Theoretically, adding different variables or group of them to the existing model can be interpreted as improvement in the model's predictive power if the pseudo R-squared in increased significantly.

For each categorical independent variable, one group is assigned as the reference group and the estimated odds ratios are compared to that reference group. In other words, the probability of observing over the probability of not observing the independent variable (unmet medical need) is compared between each of the categories and reference group. For example, if we define male as the reference group, the logistic regression output provides a coefficient that can be interpreted as probability of a female experiencing over not experiencing unmet medical need compared to a male, while controlling for other independent variables in the model. If the value is greater than one (e.g. two) and significant ($p$ value $< 0.05$), it means, controlling for the other variables in the model, women are two times more likely to report experiencing unmet medical need than men.

Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) statistics along with Pseudo R-squared values resulted from each model are compared to several nested and hierarchical models. Because all models estimated the association with the same dependent variable, Pseudo R-squared can be used to compare the relative importance of the predictors in each model based on the contribution to the explained variance. Additionally, lower values of AIC and BIC represent the improvement in model fitting. Generally, by including extra variables in new models, lower AIC and BIC values and higher Pseudo R-squared values are optimum (Burnham & Anderson, 2004; Raftery, 1995). That is, since we are measuring the same dependent variable using different models, these statistics are more reliable and comparable than if the aim of the models was to predict different dependent variables. AIC and BIC penalize the likelihood of the model fit by incorporating the effects of the added parameters. That is, these test statistics aim to adjust for added variables and prevent inflated likelihood results. In hierarchical models, gradual decline in the AIC and BIC values along with a gradual rise in the value of the Pseudo R-squared is optimum.

## CART and CHAID Analyses

Classification and regression Tress (CART) and Chi-square Automatic Interaction (CHAID) are tools that are used in machine learning, data mining, statistics, computer science, and several other fields. Both tools give a decision tree output to estimate the relative importance of several variables in predicting a binary or continuous dependent variable.

Theoretically, both models are similar to other statistical tools and methods such as regression analysis. However, contrary to most of the regression analysis methods, CART and CHAID do not have a lot of restrictive assumptions about the distribution of data. The principal notion of these approaches is to split the predictor variables in a way that the most important predictors are identified based on the relative importance in predicting the outcome variable. That is, by identifying the different values (or ranges) of given predictors, we are more likely to predict the value of, for example, a binary outcome variable correctly.

The classic example of the application of CART is the prediction of the survival or death of the passengers of the RMS Titanic shipwreck. The dichotomous outcome variable is coded as 1 (survived) and 0 (died). Different variables such as the passenger's age, cabin class, and number of the siblings or female family members in the ship are used as the predictors of the survival or death.

Theoretically, analysis trees keep splitting and generating new leaves (nodes) until there is no observations under each leaf (child) node to further split. To prevent over fitting and having trees with excessive leaves, especially in large datasets, pruning and stopping rules are usually set based on the absolute frequency or percentage of observation within each parent or child node and the p-value. These approaches make the output more compact and comparable.

For example, the stopping rules can be set to stop splitting after there is at least 2% of the whole observation in a parent node, 1% of observations in a child node, and discrimination p-value for splitting is less than .05. Overfitting happens when the models are good in fitting training data. However, by introducing the testing data, these overfitted models fail to explain a large proportion of the variance and result in higher sum of residuals squared.

CART and CHAID are visually similar. However, each technique uses different approaches in splitting the nodes based on the partitioning and discrimination. For a binary outcome variable, CART usually uses GINI impurity to split the predictor variables into two groups in relation to the outcome variable. GINI impurity reaches zero when all the cases in the child node fall under one category, and CART stops splitting. For a continuous outcome variable, variance reduction is used to decide the splitting variables and points. CHAID, on the other hand, uses chi-square test to base the decision for splitting and can split to more than two groups in every split depending on the predefined pruning, stopping, and significance rules and thresholds. A CART structure is shown in Figure 7.

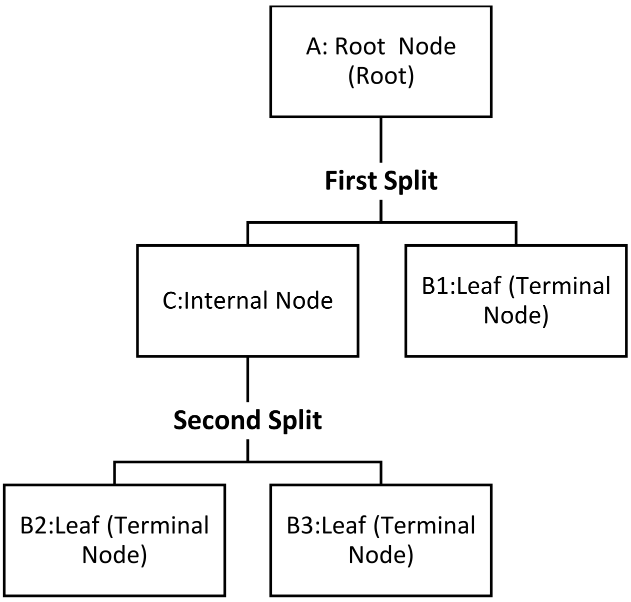


*Figure 7. Classification and Regression Tree*
Note. Node C is parent to nodes B2 and B3. Similarly, node C is a child to node A.

Data are partitioned into two groups of training and testing data. This is an essential step in using machine learning techniques in analyzing big data. Using only one set of data to produce predictive models can result in overfitted models. That is, the algorithms try to fit the best model to predict a target variable using several independent variables with higher precision and accuracy. This concept might not seem problematic in the first place. However, an overfitted model with no or weak predictive power using a new set of similar data is not a reliable model. Double checking the predictive accuracy of the model using other sets of data (i.e. testing data) can reveal if the estimated model stays consistent in predicting the target variable with different sets of data or not. It is recommended to set the testing partition proportionately higher if the observation to variable ratio is low. For example, 80% of cases can be set as training data and the other 20% of cases can be used to test the generated trees. Additionally, the trees can be trained with introduction of new data to improve the overall prediction power.

Several statistics and tests such as information Gain and Lift charts are used to compare the fitness and predictive power of the fitted models (trees). These indicators compare the marginal improvement in predicting the dependent variable using the trained tree versus using the baseline model of the mean of the outcome variable in the population.

# CHAPTER FOUR: RESULTS

## Introduction

This chapter begins with presenting descriptive statistics of the study variables. Then, national estimates of each variable and four-year trend and change in the variables are presented. The next section includes the results from logistic regression, CART, and CHAID models to test the research hypotheses. This chapter ends with a conclusion about all tested hypotheses.

## Descriptive Analysis

### Unweighted Sample and Four-Year National Estimates

Table 2 presents the unweighted and weighted frequencies and percentages for the study variables among the sample of civilian noninstitutionalized U.S. adults. Unweighted frequencies are based on the total size of the four-year pooled sample. Weighted frequencies are estimated based on the four-year average U.S. adult population. The sample size was 296,301 and the average noninstitutionalized U.S. adult population for these four years (2014 to 2017) was 243,232,150.

The percentage difference between unweighted and weighted values indicate the non-randomized multi-stage complex sampling method and oversampling of several under-represented groups such as older Blacks and Asians. Over-sampled and under-sampled groups can be identified by comparing the corresponding unweighted and weighted percentages.

Regarding the dependent variable of the study, about 9% of adults experienced unmet medical need. That is approximately an average of slightly below 22 million adults.

Regarding the predisposing variables, females constituted slightly above half of the adult population (51.78%). The four-year adult population was, approximately, proportionately distributed among the three age groups. Within a range of less than 2% difference, approximately one-third of the adult population belonged to each age group of young adults, middle-aged adults, and old adults.

Less than 13% of adults did not have a high school diploma, and slightly over 11% of them had a master's degree or higher. More than half (53.84%) of the adults were married. Regarding the ethnic-racial combination of U.S. adults, Non-Hispanic White accounted for approximately 65%. About 17.6% of adults were born in foreign countries and approximately 8% were not U.S. citizens.

In terms of the income distribution and poverty, about 20% of adults were living in families with income of 1.38 of the Federal Poverty Level (FPL) and below. Around 40% of adults were from families with income to FPL ratio of over four (family income was four times higher than federal poverty level guidelines).

About 11% (N=26,638,900) of U.S. adults had health insurance coverage. Over 64% had private health insurance coverage. Meanwhile, 20.95% were covered by Medicare, and 14.14% were covered by Medicaid or other public insurance plans. Only 2.57% of adults obtained insurance coverage through The Affordable Care Act's Market Exchange.

Slightly over 15% of adults had at least one limitation due to one or more physical or mental conditions. 8.24% have been hospitalized over-night within the last 12 months. Above 12% had fair or poor health status and more than 28% had excellent health status.

The NHIS sample size per year (unweighted) decreased from 2014 to 2017. However, the weighted percentage shows a slight increase in the U.S. adult population per year (from 24.61% in 2014 to 25.13% in 2017). Northeast and South regions account for the regions with the least (18.17%) and the most (36.69%) adult population respectively.

*Table 2. Unweighted and weighted characteristics of the civilian noninstitutionalized U.S. adults 2014-2017 (N=296,301)*

| Variable | Unweighted (Sample) | | Weighted (U.S. Adult Population) | |
|---|---|---|---|---|
| | N | % | N | % |
| Unmet Medical Need | | | | |
| No | 268,532 | 90.63 | 221,317,150 | 90.89 |
| Yes | 27,468 | 9.27 | 21,915,000 | 9 |
| Gender | | | | |
| Male | 140,691 | 47.48 | 117,415,700 | 48.22 |
| Female | 155,610 | 52.52 | 126,084,300 | 51.78 |
| Age | | | | |
| Young Adults (18-35) | 88,960 | 30.02 | 77,311,250 | 31.75 |
| Middle-aged Adults (36-55) | 101,807 | 34.36 | 82,570,850 | 33.91 |
| Old Adults (55+) | 105,534 | 35.62 | 83,617,900 | 34.34 |
| Education | | | | |
| Less than high school | 40,003 | 13.5 | 30,291,400 | 12.44 |
| High school | 69,507 | 23.46 | 56,248,500 | 23.1 |
| Some College | 64,708 | 21.84 | 52,863,850 | 21.71 |
| AA | 32,567 | 10.99 | 26,517,150 | 10.89 |
| Bachelor’s | 54,250 | 18.31 | 46,971,150 | 19.29 |
| Master's or Higher | 31,301 | 10.56 | 27,223,300 | 11.18 |
| Family Structure | | | | |
| Married | 161,355 | 54.46 | 131,100,400 | 53.84 |
| Widowed/Divorced/ Separated | 49,774 | 16.8 | 39,227,850 | 16.11 |
| Living with partner | 22,231 | 7.5 | 18,189,450 | 7.47 |
| Never married | 62,128 | 20.97 | 54,300,500 | 22.3 |
| Race / Ethnicity | | | | |
| Non-Hispanic White | 185,449 | 62.59 | 157,544,500 | 64.7 |
| Non-Hispanic Black | 34,145 | 11.52 | 28,538,200 | 11.72 |
| Hispanic | 50,638 | 17.09 | 38,132,100 | 15.66 |
| Non-Hispanic Asian | 18,228 | 6.15 | 13,879,500 | 5.7 |
| Non-Hispanic Other | 7,841 | 2.65 | 5,405,700 | 2.22 |
| Citizenship | | | | |
| US born & U.S. Citizen | 241,638 | 81.55 | 199,523,900 | 81.94 |
| Foreign Born & U.S. Citizen | 27,605 | 9.32 | 23,035,100 | 9.46 |
| Foreign Born & Non-US Citizen | 25,742 | 8.69 | 19,796,550 | 8.13 |
| Ratio of Family Income to Poverty Guidelines | | | | |
| 1.38 and Below | 61,510 | 20.76 | 47,677,300 | 19.58 |
| 1.39 to 2 | 35,171 | 11.87 | 27,539,850 | 11.31 |
| 2.01 to 4 | 88,823 | 29.98 | 72,100,350 | 29.61 |
| Above 4 | 110,797 | 37.39 | 96,182,500 | 39.5 |
| Health Insurance** | | | | |
| NO Coverage | 34,194 | 11.54 | 26,638,900 | 10.94 |
| Private | 186,057 | 62.79 | 156,619,200 | 64.32 |
| Medicare | 65,244 | 22.02 | 51,013,250 | 20.95 |
| Medicaid & other public Coverage | 43,135 | 14.56 | 34,430,900 | 14.14 |
| Market Exchange | 7,042 | 2.38 | 6,257,950 | 2.57 |
| Any limitation | | | | |
| No | 249,226 | 84.11 | 206,220,150 | 84.69 |
| Yes | 46,771 | 15.78 | 37,036,350 | 15.21 |
| Overnight Hospitalization past 12 months | | | | |
| No | 270,928 | 91.44 | 223,094,700 | 91.62 |
| Yes | 25,019 | 8.44 | 20,064,400 | 8.24 |
| Health Status | | | | |
| Excellent | 81,991 | 27.67 | 69,811,450 | 28.67 |
| Very good | 94,193 | 31.79 | 78,260,900 | 32.14 |
| Good | 81,184 | 27.4 | 64,868,400 | 26.64 |

| Variable | Unweighted (Sample) | | Weighted (U.S. Adult Population) | |
|---|---|---|---|---|
| | N | % | N | % |
| Fair | 29,700 | 10.02 | 23,302,950 | 9.57 |
| Poor | 8,847 | 2.99 | 6,939,750 | 2.85 |
| Data Year | | | | |
| 2014 | 83,939 | 28.33 | 239,700,000 | 24.61 |
| 2015 | 78,109 | 26.36 | 242,500,000 | 24.9 |
| 2016 | 74,175 | 25.03 | 245,100,000 | 25.17 |
| 2017 | 60,078 | 20.28 | 246,700,000 | 25.13 |
| Region | | | | |
| Northeast | 50,069 | 16.9 | 44,243,950 | 18.17 |
| North, Central, and Midwest | 61,504 | 20.76 | 53,764,800 | 22.08 |
| South | 103,815 | 35.04 | 89,340,150 | 36.69 |
| West | 80,913 | 27.31 | 56,151,100 | 23.06 |

Four-year Changes and Trends in U.S. Adult Population Characteristics

Table 3 shows the weighted characteristics of the civilian noninstitutionalized U.S. adults for each year from 2014 to 2017. The percentage of adults with unmet medical need decreased from 9.86% in 2014 to 8.58% in 2016 (over 1% decline); however, as shown in Figure 8, this percentage raised slightly back to 8.86% in 2017.

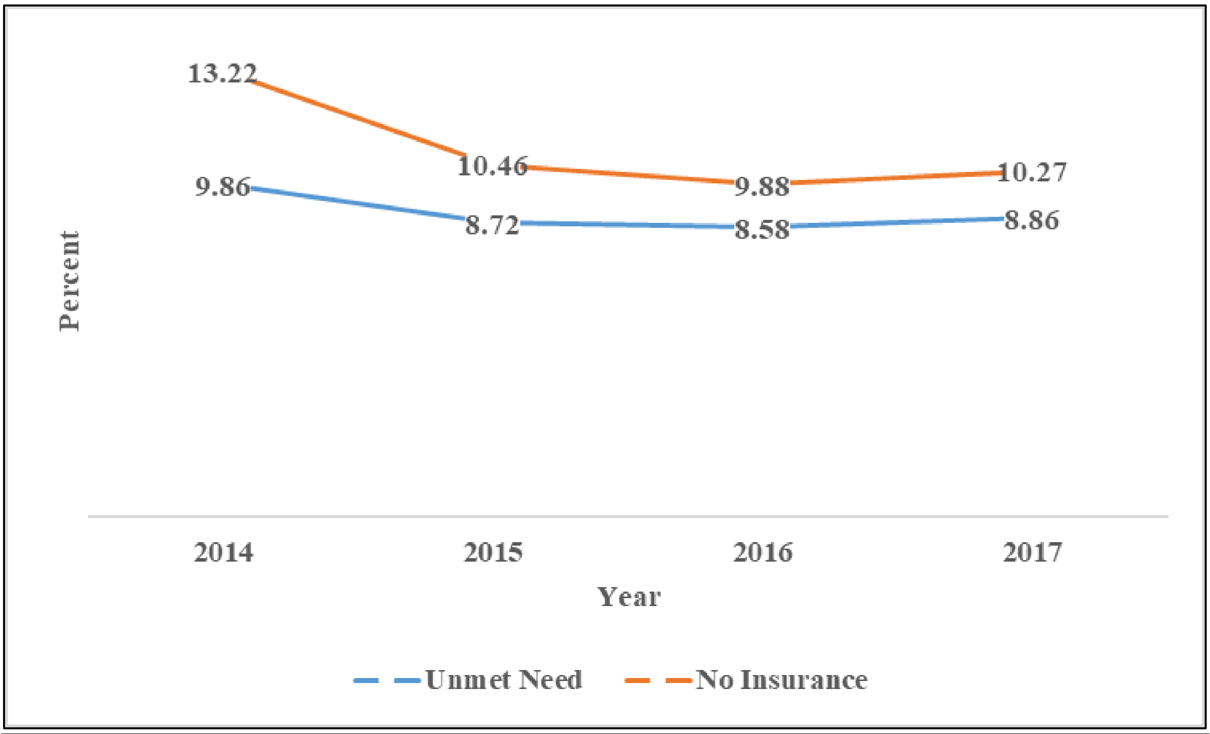


*Figure 8. Changes in the percentage of U.S. adults with unmet medical need and no health insurance coverage from 2014 to 2017*

As shown in Figure 9, age trends among U.S. adults indicate a growth towards older adult population from 2014 to 2017. The percentage of young and middle-aged adults (18 to 35 years old) declined by over 1%. At the same time, the percentage of old adults (over 55 years old) increased by a little below 2%.

*Table 3.Yearly estimates of civilian noninstitutionalized U.S. adult population characteristics (2014-2017)*

| | 2014 | | 2015 | | 2016 | | 2017 | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **N** | **%** | **N** | **%** | **N** | **%** | **N** | **%** |
| U.S. Adult Population (in Thousands) | 239700 | | 242500 | | 245100 | | 246700 | |
| Unmet Medical Need | | | | | | | | |
| No | 215,730 | 90 | 221,087 | 91.17 | 223,801 | 91.31 | 224,620 | 91.05 |
| Yes | 23,634 | 9.86 | 21,146 | 8.72 | 21,030 | 8.58 | 21,858 | 8.86 |
| Gender | | | | | | | | |
| Male | 115,535 | 48.2 | 116,885 | 48.2 | 118,212 | 48.23 | 119,008 | 48.24 |
| Female | 124,165 | 51.8 | 125,615 | 51.8 | 126,888 | 51.77 | 127,692 | 51.76 |
| Age | | | | | | | | |
| Young Adults (18-35) | 76,368 | 31.86 | 77,188 | 31.83 | 77,844 | 31.76 | 77,834 | 31.55 |
| Middle-aged Adults (36-55) | 83,080 | 34.66 | 82,741 | 34.12 | 82,378 | 33.61 | 82,028 | 33.25 |
| Old Adults (55+) | 80,252 | 33.48 | 82,571 | 34.05 | 84,878 | 34.63 | 86,814 | 35.19 |
| Education | | | | | | | | |
| Less than high school | 31,616 | 13.19 | 30,555 | 12.6 | 30,123 | 12.29 | 28,889 | 11.71 |
| High school | 56,929 | 23.75 | 55,702 | 22.97 | 56,054 | 22.87 | 56,272 | 22.81 |
| Some College | 52,590 | 21.94 | 52,986 | 21.85 | 53,628 | 21.88 | 52,276 | 21.19 |
| AA | 25,360 | 10.58 | 26,336 | 10.86 | 26,765 | 10.92 | 27,606 | 11.19 |
| Bachelor’s | 43,961 | 18.34 | 46,730 | 19.27 | 47,819 | 19.51 | 49,365 | 20.01 |
| Master's or Higher | 25,216 | 10.52 | 26,675 | 11 | 27,770 | 11.33 | 29,259 | 11.86 |
| Family Structure | | | | | | | | |
| Married | 129,198 | 53.9 | 131,096 | 54.06 | 132,133 | 53.91 | 131,935 | 53.48 |
| Widowed/Divorced/ Separated | 38,831 | 16.2 | 39,358 | 16.23 | 38,799 | 15.83 | 39,891 | 16.17 |
| Living with partner | 17,594 | 7.34 | 17,557 | 7.24 | 18,652 | 7.61 | 18,947 | 7.68 |
| Never married | 53,333 | 22.25 | 53,762 | 22.17 | 54,878 | 22.39 | 55,236 | 22.39 |
| Race / Ethnicity | | | | | | | | |
| Non-Hispanic White | 157,459 | 65.69 | 157,480 | 64.94 | 157,697 | 64.34 | 157,493 | 63.84 |
| Non-Hispanic Black | 27,949 | 11.66 | 28,470 | 11.74 | 28,726 | 11.72 | 29,037 | 11.77 |
| Hispanic | 36,578 | 15.26 | 37,757 | 15.57 | 38,775 | 15.82 | 39,423 | 15.98 |
| Non-Hispanic Asian | 13,112 | 5.47 | 13,677 | 5.64 | 14,265 | 5.82 | 14,531 | 5.89 |
| Non-Hispanic Other | 4,602 | 1.92 | 5,117 | 2.11 | 5,637 | 2.3 | 6,242 | 2.53 |
| Citizenship | | | | | | | | |
| US born & U.S. Citizen | 196,506 | 81.98 | 198,996 | 82.06 | 200,541 | 81.82 | 202,047 | 81.9 |
| Foreign Born & U.S. Citizen | 21,837 | 9.11 | 22,504 | 9.28 | 23,897 | 9.75 | 23,881 | 9.68 |
| Foreign Born & Non-US Citizen | 20,159 | 8.41 | 19,909 | 8.21 | 19,608 | 8 | 19,489 | 7.9 |
| Ratio of Family Income to Poverty Guidelines | | | | | | | | |
| 1.38 and Below | 50,337 | 21 | 47,870 | 19.74 | 47,304 | 19.3 | 45,195 | 18.32 |
| 1.39 to 2 | 27,805 | 11.6 | 27,548 | 11.36 | 27,745 | 11.32 | 27,063 | 10.97 |
| 2.01 to 4 | 72,365 | 30.19 | 72,023 | 29.7 | 71,741 | 29.27 | 72,283 | 29.3 |
| Above 4 | 89,192 | 37.21 | 95,060 | 39.2 | 98,285 | 40.1 | 102,158 | 41.41 |
| Health Insurance** | | | | | | | | |
| NO Coverage | 31,688 | 13.22 | 25,366 | 10.46 | 24,216 | 9.88 | 25,336 | 10.27 |
| Private | 151,658 | 63.27 | 156,922 | 64.71 | 158,923 | 64.84 | 158,973 | 64.44 |
| Medicare | 48,347 | 20.17 | 50,076 | 20.65 | 52,304 | 21.34 | 53,337 | 21.62 |

| Variable | 2014 N | 2014 % | 2015 N | 2015 % | 2016 N | 2016 % | 2017 N | 2017 % |
|---|---|---|---|---|---|---|---|---|
| Medicaid & other public Coverage | 31,233 | 13.03 | 34,556 | 14.25 | 36,275 | 14.8 | 35,623 | 14.44 |
| Market Exchange | 4,339 | 1.81 | 6,014 | 2.48 | 7,157 | 2.92 | 7,524 | 3.05 |
| Any limitation | | | | | | | | |
| No | 204,129 | 85.16 | 206,004 | 84.95 | 206,987 | 84.45 | 207,746 | 84.21 |
| Yes | 35,308 | 14.73 | 36,254 | 14.95 | 37,794 | 15.42 | 38,757 | 15.71 |
| Overnight Hospitalization past 12 months | | | | | | | | |
| No | 219,829 | 91.71 | 222,082 | 91.58 | 224,879 | 91.75 | 225,607 | 91.45 |
| Yes | 19,464 | 8.12 | 20,079 | 8.28 | 19,927 | 8.13 | 20,821 | 8.44 |
| Health Status | | | | | | | | |
| Excellent | 70,520 | 29.42 | 69,961 | 28.85 | 69,437 | 28.33 | 69,298 | 28.09 |
| Very good | 75,434 | 31.47 | 76,460 | 31.53 | 80,564 | 32.87 | 80,572 | 32.66 |
| Good | 64,024 | 26.71 | 65,184 | 26.88 | 64,608 | 26.36 | 65,622 | 26.6 |
| Fair | 22,388 | 9.34 | 23,523 | 9.7 | 23,481 | 9.58 | 23,856 | 9.67 |
| Poor | 6,951 | 2.9 | 7,057 | 2.91 | 6,765 | 2.76 | 6,932 | 2.81 |
| Region | | | | | | | | |
| Northeast | 42,163 | 17.59 | 42,947 | 17.71 | 46,201 | 18.85 | 45,689 | 18.52 |
| North, Central, and Midwest | 54,268 | 22.64 | 53,302 | 21.98 | 53,383 | 21.78 | 54,101 | 21.93 |
| South | 89,408 | 37.3 | 90,598 | 37.36 | 88,089 | 35.94 | 89,281 | 36.19 |
| West | 53,861 | 22.47 | 55,654 | 22.95 | 57,451 | 23.44 | 57,629 | 23.36 |

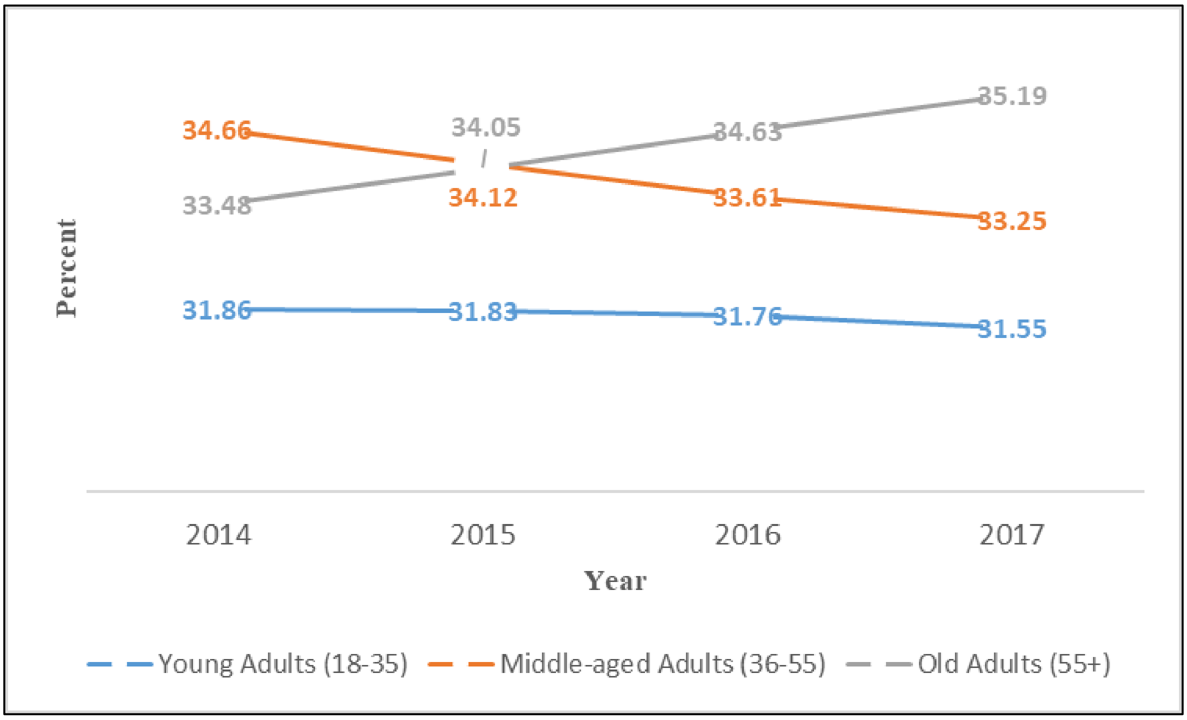


*Figure 9. Changes in the percentage of U.S. Adults in different age group from 2014 to 2017*

An overview of the changes in the percentage of adults with different educational attainment from 2014 to 2017 indicate a noticeable raise in the proportion of adults with degrees from higher educational institutions (over 1% increase from 2014 to 2017 in each group). At the same time, the proportion of adults with some college, high school, and less than high school educational attainment declined about 1%.

The proportionate share of different family structures among adults does not show a clear trend. Rather, fluctuations exist form one year to another in the percentage of married and never-married adults and other categories.

The percentage of Non-Hispanic White compared to other ethnoracial groups is decreased by a slightly below 2%. On the other hand, other racial groups' contribution to adult population raised proportionate to decline in White adult population (Figure 10).

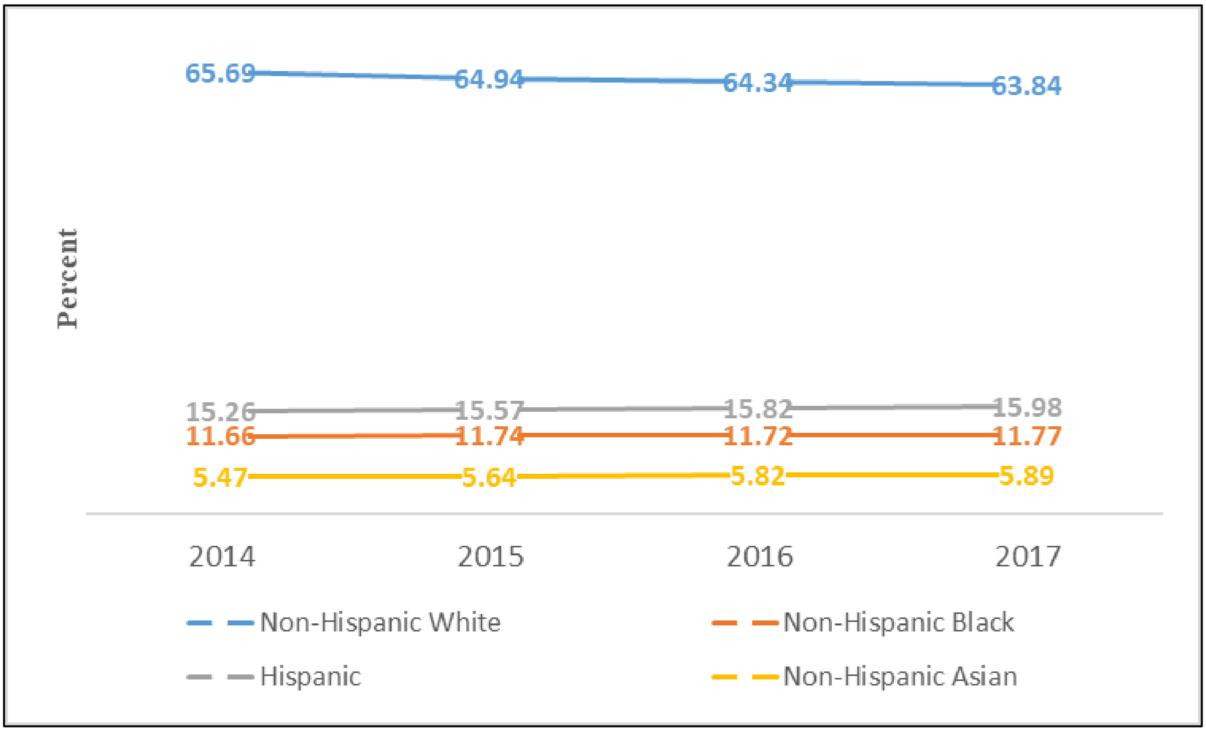


*Figure 10. Changes in the ethnoracial combination of U.S. adults from 2014 to 2017*

The share of Foreign-born non-U.S. citizen in adult population declined by .5% from 2014 to 2017. The four-year changes in two other categories, U.S. citizen born in U.S. and overseas, did not show a constant upward or downward trend (Figure 11).

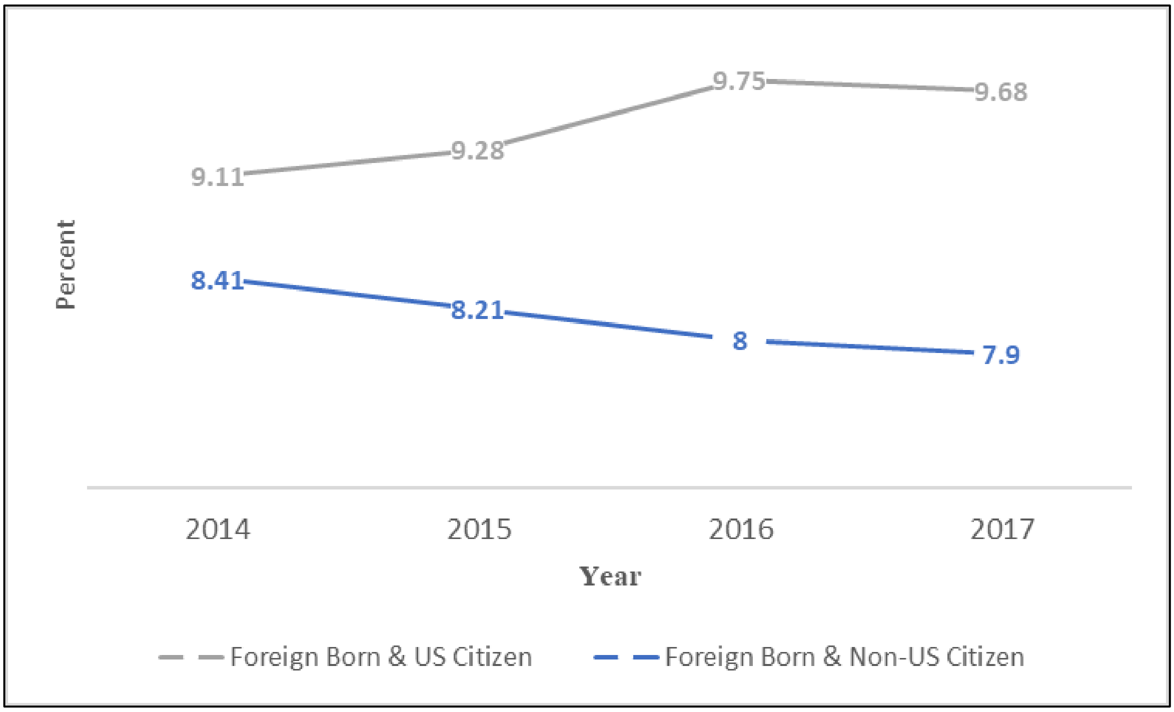


*Figure 11. Changes in the percentage of foreign-born U.S. adults from 2014 to 2017*

Figure 12 shows the percentage of adults in four different groups of the ratio of family income to federal poverty level. From 2014 to 2017 the proportion of adults living in families with income to FPL ratio of below 4 decreased. At the same time, the proportion of adults living in higher income categories (about 4 times and more above FPL) raised by more than 4%.

Regarding the health insurance coverage, as shown in Figure 13, the percentage of U.S. adults with no insurance coverage declined by about 2% from 13.22% in 2014 to 10.27% in 2017. The beneficiaries of ACA's insurance market exchanges also increased from 1.81% to 3.05%. Compared to 2016 and before, in 2017, except for market exchange coverage, the trend of increase in health insurance coverage and decrease in uninsured adult population shifted the direction toward decline in the percentage of covered adults.

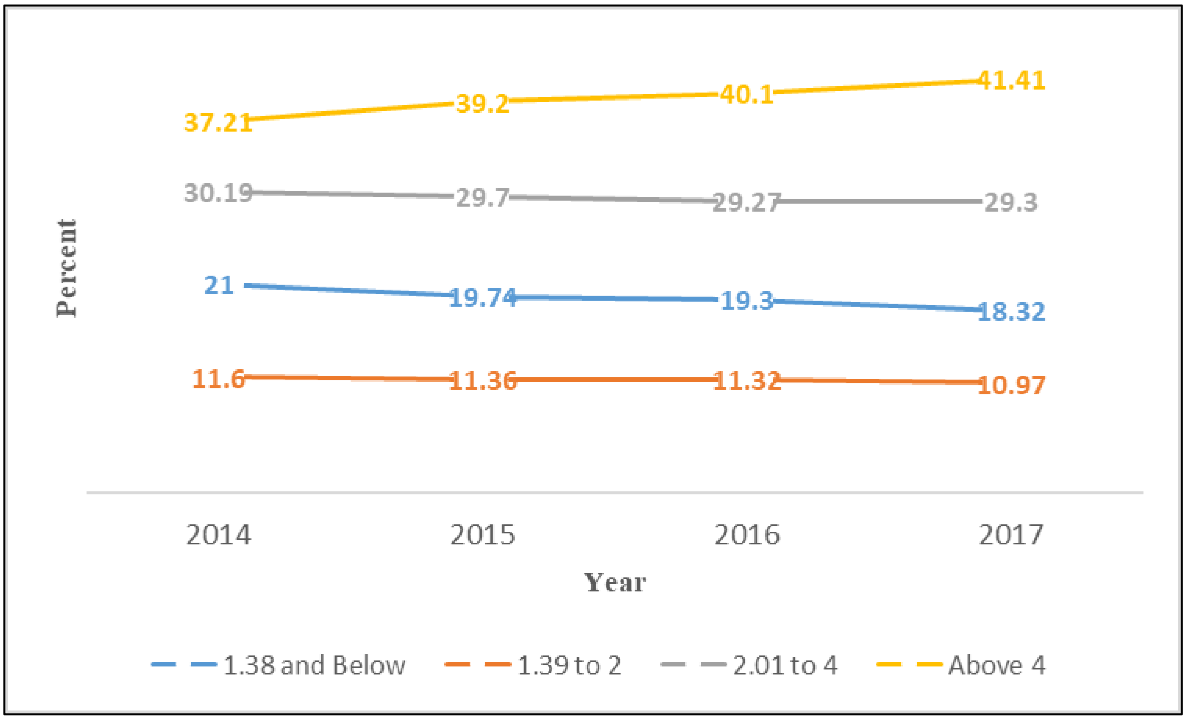


*Figure 12. Changes in the percentage of U.S. adults with the different family income ratio to federal poverty level from 2014 to 2017*

Percentage of adults with physical or mental limitation or overnight hospitalization in last 12 months increased about 1% and .5% from 2014 to 2017 respectively. In terms of the perceived health status among adults, trends similar to health insurance coverage were observed (Figure 14). That is, percentage of adults with excellent and very good health status increased from 2014 to 2016 and declined in 2017. At the same time, percentage of adults with poor health status decreased from 2014 to 2016 and raised slightly in 2017.

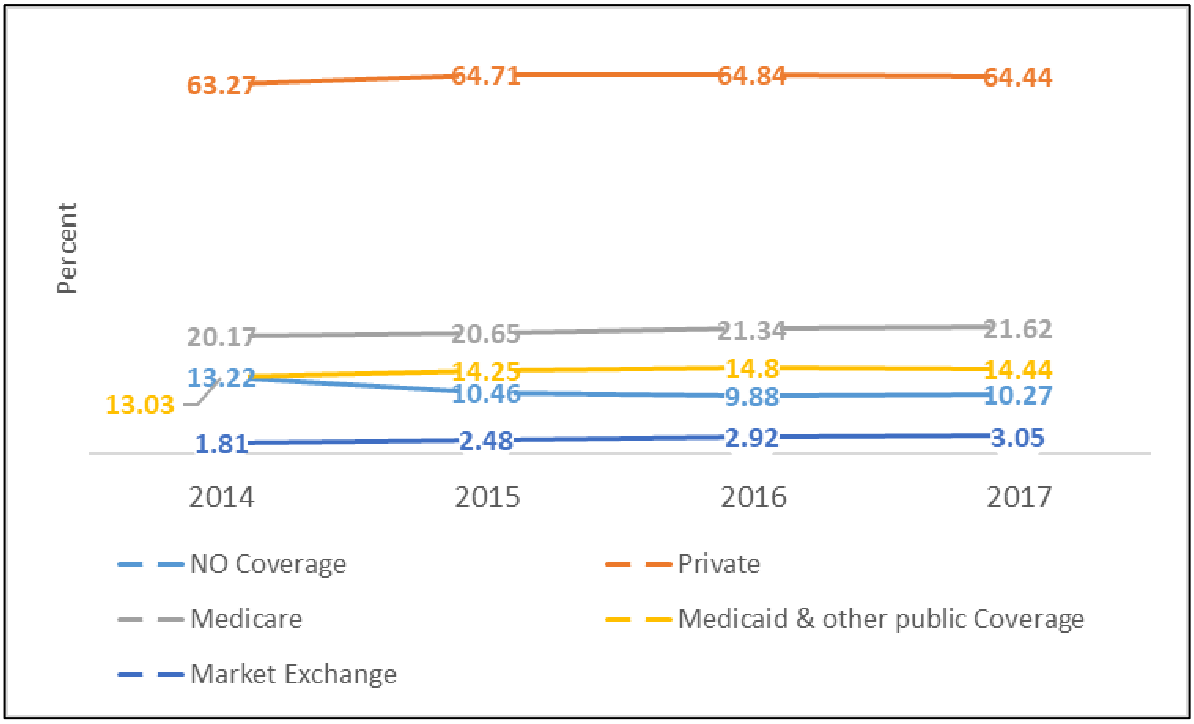


*Figure 13. Changes in health insurance coverage type and status of U.S. adults from 2014 to 2017*

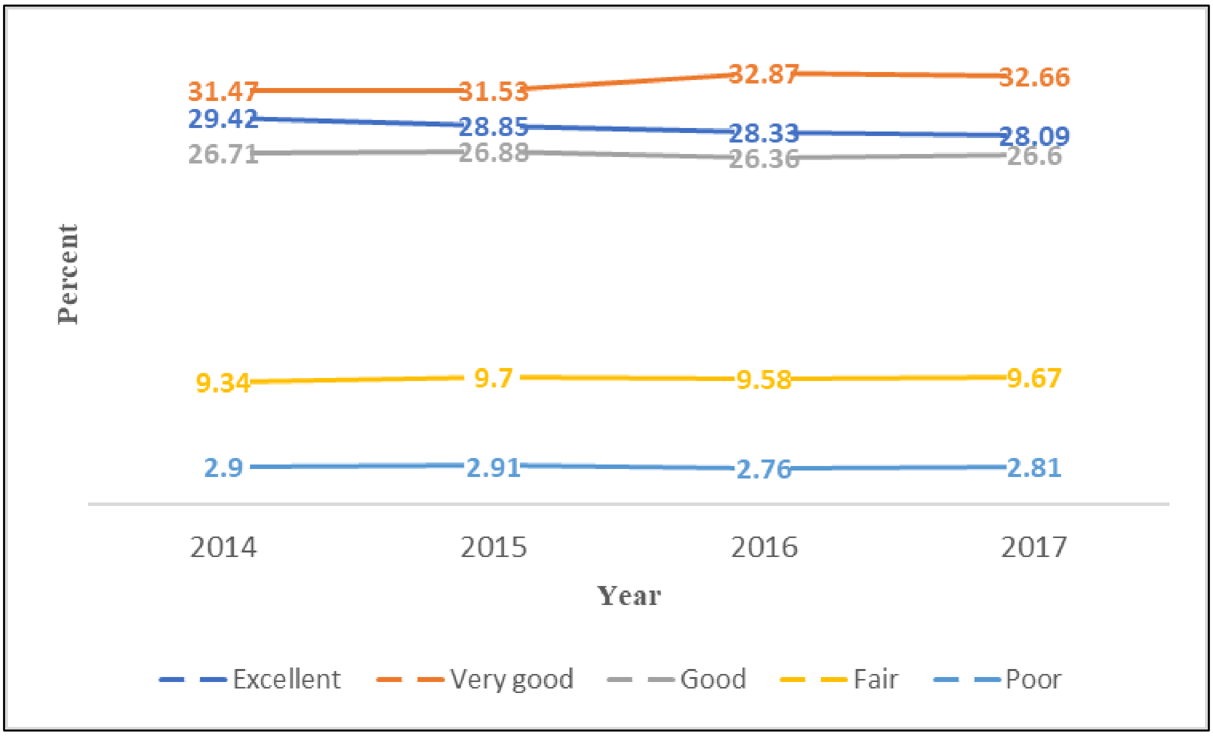


*Figure 14. Changes in perceived health status of U.S. adults from 2014 to 2017*

## Regression Analysis

### Logistic Regressions with Single Predictor and Multiple Predictors

To compare the association of unmet medical need with different groups of predisposing, enabling, need, and policy proxies (year and region) variables, separate logistic regression models were used. Then, hierarchical models by adding one group of variables at time were performed. Results from the single category models, hierarchical models, and the full model are compared to conclude about the relative importance of the predisposing, enabling, and need factors in association with unmet medical need. At the end of this section, a comprehensive table is presented to compare the models and conclude on the tested hypotheses.

Table 4 shows the odds ratios and corresponding 95% confidence intervals for the association between unmet medical need and predisposing variables including gender, age, educational attainment, family structure, race and ethnicity, and residency status (Model 1). Almost all odds ratios were significant at $p<.001$. The odds ratio for comparing Hispanic to Non-Hispanic White is significant at $p<.05$. The Odds ratios for non-Hispanic Black and some college education were not statistically significant.

In general, females were more likely to experience unmet medical need than males (OR:1.17, 95%CI:1.14-1.2). Compared to young adults and older adults, middle-aged adults were more likely to report unmet medical need (OR:1.33, 95%CI:1.27-1.39). Higher levels of educational attainment were inversely associated with unmet medical need. Those with higher educational attainment were less likely to have unmet medical need than their less educated counterparts. Compared to others, married individuals had significantly less chances of experiencing unmet medical need. Compared to U.S. born citizen, those who were born abroad but where U.S. citizen at the time of the interview, were less likely to have unmet medical need

(OR:.88, 95%CI:.82-.95). However, those who have not became a U.S. citizen yet, were more likely to have unmet medical needs than U.S. born adults.

*Table 4. Results from logistic regression: model (1) the association between unmet medical need and predisposing variables*

| **Variable (Reference Group)** | OR | 95% CI |
|---|---|---|
| Gender (Male) | | |
| Female | 1.17 | 1.14-1.2 |
| Age (Young Adults (18-35)) | | |
| Middle-aged Adults (36-55) | 1.33 | 1.27-1.39 |
| Old Adults (55+) | .75 | .71-.8 |
| Education (Less than high school) | | |
| High school | .74 | .7-.78 |
| Some College | .96† | .91-1.01 |
| AA | .86 | .81-.91 |
| Bachelor’s | .59 | .55-.63 |
| Master's or Higher | .46 | .43-.5 |
| Family Structure (Married) | | |
| Widowed/Divorced/ Separated | 2.06 | 1.96-2.16 |
| Living with partner | 1.73 | 1.62-1.84 |
| Never married | 1.51 | 1.44-1.6 |
| Race / Ethnicity (Non-Hispanic White) | | |
| Non-Hispanic Black | 1.05† | .99-1.11 |
| Hispanic | .91* | .86-.97 |
| Non-Hispanic Asian | .54 | .49-.6 |
| Non-Hispanic Other | 1.31 | 1.17-1.47 |
| Citizenship (US born & U.S. Citizen) | | |
| Foreign Born & U.S. Citizen | .88 | .82-.95 |
| Foreign Born & Non-US Citizen | 1.27 | 1.18-1.37 |

Note. All Odds Ratios are significant at p<.001, except:
*Significant at p<.05
†Non-significant

Odds ratios and corresponding 95% confidence intervals for the second logistic regression model (Model 2) that only included enabling factors (i.e. family income to FPL ratio and health insurance), is presented in Table 5. Adults with higher family income to FPL ratio were less likely to have unmet medical need. For example, compared to those with a family income below 1.39 FPL, those with family income to FPL ratio of above four were almost three time less likely to have unmet medical need (OR: .34, 95%CI: .32-.36).

Odds ratios for different groups of health insurance indicate that adults without any type of health insurance coverage were almost 3.5 times more likely to have unmet medical need than those with at least one type of health insurance coverage (OR: 3.51, 95%CI:3.26-3.77).

Those with private or Medicare coverage were also less likely to have unmet medical need (OR were .85 and .7 respectively). Those who obtained health insurance coverage through ACA's Market Exchange were more likely to have unmet medical need (OR: 1.24, 95%CI: 1.12-1.38).

*Table 5. Results from logistic regression: model (2) the association between unmet medical need and enabling variables*

| **Variable (Reference Group)** | OR | 95% CI |
|---|---|---|
| Family Income to Poverty Ratio (1.38 and Below) | | |
| 1.39 to 2 * | .94 | .89-1 |
| 2.01 to 4 | .71 | .68-.75 |
| Above 4 | .34 | .32-.36 |
| Health Insurance | | |
| NO Coverage | 3.51 | 3.26-3.77 |
| Private | .85 | .8-.9 |
| Medicare | .7 | .66-.74 |
| Medicaid & other public Coverage † | .93 | .86-1 |
| Market Exchange | 1.24 | 1.12-1.38 |

Note. Because several respondents reported more than one type of health insurance coverage, categories of health insurance are coded as dichotomous and no group is assigned as reference.
All Odds Ratios are significant at $p<.001$, except:
*Significant at $p<.05$
†Non-significant

Table 6 shows the association between unmet medical need and health care need variables including existence of physical or mental limitations, overnight hospitalization in the past 12 months, and respondent-evaluated health status (Model 3). Those with at least one type of physical or mental limitation were more likely to have unmet medical need than those without any similar limitations (OR: 1.36, 95%CI:1.3-1.43). The chances of experiencing unmet medical need among people with at least one overnight hospitalization in the last 12 months was slightly less than those without overnight hospitalization (OR: .92, 95%CI: .88-.98). Compared to those with poor health status, other categories of perceived health status from fair to excellent were less likely to experience unmet medical need.

Results of the logistic regression for the association between unmet medical need and year and region variables are presented in Table 7 (Model 4). Compared to 2014, U.S. adults were less likely to have unmedical need in upcoming years of 2015 to 2017.

*Table 6. Results from logistic regression: model (3) the association between unmet medical need and need variables*

| **Variable (Reference Group)** | OR | 95% CI |
|---|---|---|
| Any limitation (No) | | |
| Yes | 1.36 | 1.3-1.43 |
| Hospitalization (No) | | |
| Yes | .92* | .88-.98 |
| Health Status (Poor) | | |
| Fair | .83 | .77-.9 |
| Good | .53 | .49-.57 |
| Very good | .33 | .31-.36 |
| Excellent | .21 | .19-.23 |

Note: All Odds Ratios are significant at p<.001, except:
*Significant at p<.05

Residents of North, Central, Midwest, South, and West regions were more likely than those resided in Northeast region to experience unmet medical need.

*Table 7. Results from logistic regression: model (4) the association between unmet medical need and year and region variables*

| **Variable (Reference Group)** | OR | 95% CI |
|---|---|---|
| Year (2014) | | |
| 2015 | .87 | .83-.92 |
| 2016 | .86 | .81-.91 |
| 2017 | .89 | .84-.94 |
| Region (Northeast) | | |
| North, Central, & Midwest | 1.42 | 1.32-1.53 |
| South | 1.62 | 1.51-1.73 |
| West | 1.36 | 1.25-1.47 |

Note. All Odds Ratios are significant at p<.001.

Table 8. compares the results of logistic regression for two types of models. In the single predictor models, association between unmet medical need and each variable are tested separately and resulted odds ratios and corresponding 95% confidence intervals are reported. On the other hand, in the full model, all the predictors are simultaneously entered to a regression model to estimate the joint association of the variables with unmet medical need. Comparing the full model to single variable and four previous models (with predisposing, enabling, need, and year-region) indicate no change in the direction of the associations. That is, odds ratios below and above one in the single independent variable models stayed at the same position regarding to the value of one. However, after including all the variables in one logistic

regression model, the significance level, magnitude, and corresponding 95% confidence interval of the several odds ratios changed.

For example, the odds ratios (and corresponding 95% confidence intervals) for female versus male were 1.2 (1.16-1.23), 1.07 (1.14-1.2), and 1.22 (1.18-1.26) in the single-variable, predisposing variables, and full model respectively. Additionally, regarding the gender, odds ratios in all these three models were significant. ($p<.001$ in all three models). However, for example, the odds ratios for the years 2016 and 2017 (compared to 2014 as the reference year) were significant in single variable model and non-significant in the full model.

*Table 8. Results from the Logistic regression Analysis: models with a single predictor and the full model with all predictors included at once*

| Variable (Reference) | Single Predictor Models | | Full Model | |
|---|---|---|---|---|
| | OR | 95% CI | OR | 95% CI |
| Gender (Male) | | | | |
| Female | 1.2 | 1.16-1.23 | 1.22 | 1.18-1.26 |
| Age (Young Adults (18-35)) | | | | |
| Middle-aged Adults (36-55) | 1.14 | 1.1-1.18 | 1.17 | 1.11-1.22 |
| Old Adults (55+) | .72 | .69-.75 | .88 | .83-.94 |
| Education (Less than high school) | | | | |
| High school | .71 | .67-.75 | 1.01† | .95-1.07 |
| Some College | .95* | .9-1 | 1.46 | 1.38-1.55 |
| AA | .83 | .79-.88 | 1.5 | 1.41-1.6 |
| Bachelor’s | .53 | .5-.56 | 1.5 | 1.4-1.6 |
| Master's or Higher | .4 | .37-.43 | 1.46 | 1.34-1.59 |
| Family Structure (Married) | | | | |
| Widowed/Divorced/ Separated | 2.08 | 1.99-2.17 | 1.58 | 1.5-1.66 |
| Living with partner | 1.95 | 1.83-2.07 | 1.28 | 1.19-1.37 |
| Never married | 1.65 | 1.58-1.72 | 1.27 | 1.2-1.34 |
| Race / Ethnicity (Non-Hispanic White) | | | | |
| Non-Hispanic Black | 1.28 | 1.21-1.35 | .84 | .8-.89 |
| Hispanic | 1.16 | 1.1-1.23 | .7 | .66-.75 |
| Non-Hispanic Asian | .5 | .46-.55 | .56 | .5-.63 |
| Non-Hispanic Other | 1.57 | 1.41-1.74 | .91† | .79-1.04 |
| Citizenship (US born & U.S. Citizen) | | | | |
| Foreign Born & U.S. Citizen | .7 | .66-.75 | .91* | .84-.98 |
| Foreign Born & Non-US Citizen | 1.16 | 1.09-1.24 | .79 | .73-.86 |
| Ratio of Family Income to FPL (1.38 and Below) | | | | |
| 1.39 to 2 | .86 | .82-.91 | 1† | .94-1.06 |
| 2.01 to 4 | .57 | .54-.59 | .78 | .74-.82 |
| Above 4 | .24 | .22-.25 | .4 | .37-.43 |
| Health Insurance | | | | |
| NO Coverage | 5.59 | 5.36-5.83 | 5.03 | 4.67-5.42 |
| Private | .36 | .34-.37 | 1.02† | .96-1.08 |
| Medicare | .58 | .55-.6 | .44 | .41-.47 |
| Medicaid & other public Coverage | .95 | .93-.97 | .76 | .7-.82 |
| Market Exchange | 1.41 | 1.28-1.55 | 1.46 | 1.31-1.63 |

| Variable (Reference) | Single Predictor Models | | Full Model | |
|---|---|---|---|---|
| | OR | 95% CI | OR | 95% CI |
| Any limitation (No) | | | | |
| Yes | 2.39 | 2.3-2.47 | 1.92 | 1.82-2.03 |
| Hospitalization (No) | | | | |
| Yes | 1.43 | 1.36-1.51 | 1.08* | 1.02-1.14 |
| Health Status (Poor) | | | | |
| Fair | .76 | .71-.82 | .82 | .75-.89 |
| Good | .44 | .41-.47 | .5 | .46-.54 |
| Very good | .27 | .25-.29 | .34 | .31-.37 |
| Excellent | .17 | .16-.18 | .21 | .19-.23 |
| Year (2014) | | | | |
| 2015 | .87 | .83-.92 | .93* | .88-.98 |
| 2016 | .86 | .81-.91 | .95† | .89-1 |
| 2017 | .89 | .84-.94 | .98† | .93-1.03 |
| Region (Northeast) | | | | |
| North, Central, & Midwest | 1.43 | 1.33-1.54 | 1.21 | 1.12-1.3 |
| South | 1.62 | 1.51-1.73 | 1.21 | 1.13-1.3 |
| West | 1.36 | 1.25-1.47 | 1.29 | 1.19-1.4 |

Notes. All Odds Ratios are significant at $p<.001$, except:
*Significant at $p<.05$
†Non-significant
Because some adults had more than one type of health insurance coverage, categories of health insurance are dichotomized, and no group is assigned as reference group.

## Logistic Regressions with Hierarchical Models

Table 9 shows the odds ratios and corresponding 95% confidence intervals for four hierarchical logistic regression models used to measure the association between unmet medical need and the predictors. Model (1) only uses predisposing variables including gender, age, educational attainment, family structure, race-ethnicity, and U.S. residential status. Model (2) includes both predisposing and enabling variables (income and health insurance). In the third model, need variables (existence of limitations, overnight hospitalization, and perceived health status) are added to the second model. Model (4) includes all the variables in the model (3) and two variables of year and geographical region. Adding new groups of variables in each step to study the joint association of the predictors with unmet medical need, in most cases, changed the confidence interval and the numerical value of the odds ratios. Additionally, though less frequently, the significance level of several variable changed from one model to another.

For example, odds ratio and corresponding confidence intervals for middle-age adults, compared to young adults, has changed in four models, from 1.33 (1.3-1.36) to 1.17 (1.14-1.19). Similarly, for example, compared to the models 2 and 3, odds ratio for the private health insurance coverage became insignificant in the fourth model.

*Table 9. Comparing the influence of each group of variables on the association with unmet medical need with hierarchical logistic regression.*

| **Variable (Reference)** | **Model (1) OR (95% CI)** | **Model (2) OR (95% CI)** | **Model (3) OR (95% CI)** | **Model (4) OR (95% CI)** |
|---|---|---|---|---|
| Gender (Male) | | | | |
| Female | 1.17 (1.15-1.19) | 1.21 (1.19-1.23) | 1.22 (1.2-1.24) | 1.22 (1.2-1.24) |
| Age (Young Adults (18-35)) | | | | |
| Middle-aged Adults (36-55) | 1.33 (1.3-1.36) | 1.52 (1.48-1.55) | 1.16 (1.14-1.19) | 1.17 (1.14-1.19) |
| Old Adults (55+) | .75 (.73-.77) | 1.28 (1.24-1.32) | .88 (.85-.91) | .88 (.86-.91) |
| Education (Less than high school) | | | | |
| High school | .74 (.72-.76) | .9 (.88-.93) | 1** (.97-1.03) | 1.01** (.98-1.03) |
| Some College | .96* (.93-.98) | 1.29 (1.26-1.33) | 1.47 (1.42-1.51) | 1.46 (1.42-1.5) |
| AA | .86 (.84-.89) | 1.29 (1.25-1.33) | 1.5 (1.45-1.55) | 1.5 (1.45-1.55) |
| Bachelor’s | .59 (.57-.6) | 1.17 (1.14-1.21) | 1.49 (1.44-1.54) | 1.5 (1.45-1.55) |
| Master's or Higher | .46 (.44-.48) | 1.09** (1.05-1.14) | 1.45 (1.39-1.51) | 1.46 (1.4-1.52) |
| Family Structure (Married) | | | | |
| Widowed/Divorced/ Separated | 2.06 (2.01-2.1) | 1.69 (1.65-1.72) | 1.58 (1.54-1.62) | 1.58 (1.54-1.62) |
| Living with partner | 1.73 (1.68-1.78) | 1.31 (1.27-1.35) | 1.27 (1.23-1.31) | 1.28 (1.24-1.32) |
| Never married | 1.51 (1.48-1.55) | 1.28 (1.25-1.31) | 1.26 (1.23-1.29) | 1.27 (1.24-1.3) |
| Race / Ethnicity (Non-Hispanic White) | | | | |
| Non-Hispanic Black | 1.05** (1.02-1.07) | .86 (.83-.88) | .84 (.82-.86) | .84 (.82-.87) |
| Hispanic | .91 (.89-.93) | .7 (.68-.72) | .72 (.7-.74) | .7 (.68-.72) |
| Non-Hispanic Asian | .54 (.51-.56) | .58 (.55-.6) | .57 (.55-.6) | .56 (.53-.59) |

| Variable (Reference) | Model (1) OR (95% CI) | Model (2) OR (95% CI) | Model (3) OR (95% CI) | Model (4) OR (95% CI) |
|---|---|---|---|---|
| Non-Hispanic Other | 1.31 (1.25-1.37) | 1.02* (.97-1.07) | .93* (.88-.98) | .91** (.86-.95) |
| Citizenship (US born & U.S. Citizen) | | | | |
| Foreign Born & US Citizen | .88 (.85-.91) | .82 (.79-.85) | .9** (.87-.93) | .91*** (.88-.94) |
| Foreign Born & Non-US Citizen | 1.27 (1.23-1.31) | .68 (.66-.71) | .78 (.75-.81) | .79 (.76-.82) |
| Ratio of Family Income to Poverty Guidelines (1.38 and Below) | | | | |
| 1.39 to 2 | | .93* (.9-.95) | 1* (.97-1.02) | 1* (.97-1.02) |
| 2.01 to 4 | | .67 (.66-.69) | .78 (.76-.8) | .78 (.76-.8) |
| Above 4 | | .31 (.3-.32) | .4 (.39-.41) | .4 (.39-.41) |
| Health Insurance | | | | |
| NO Coverage | | 4.22 (4.08-4.36) | 5.04 (4.87-5.21) | 5.03 (4.86-5.2) |
| Private | | .85 (.82-.87) | 1.01 (.98-1.04) | 1.02* (.99-1.05) |
| Medicare | | .59 (.58-.61) | .44 (.42-.45) | .44 (.43-.45) |
| Medicaid & other public Coverage | | .94** (.91-.97) | .75 (.72-.78) | .76 (.73-.79) |
| Market Exchange | | 1.25 (1.19-1.31) | 1.45 (1.38-1.53) | 1.46 (1.39-1.53) |
| Any limitation (No) | | | | |
| Yes | | | 1.92 (1.87-1.97) | 1.92 (1.87-1.97) |
| Hospitalization (No) | | | | |
| Yes | | | 1.08*** (1.05-1.11) | 1.08*** (1.05-1.11) |
| Health Status (Poor) | | | | |
| Fair | | | .81 (.78-.84) | .82 (.78-.85) |
| Good | | | .5 (.48-.52) | .5 (.48-.52) |
| Very good | | | .34 (.32-.35) | .34 (.32-.35) |
| Excellent | | | .21 (.2-.22) | .21 (.2-.22) |
| Year (2014) | | | | |
| 2015 | | | | .93*** |

| Variable (Reference) | Model (1) OR (95% CI) | Model (2) OR (95% CI) | Model (3) OR (95% CI) | Model (4) OR (95% CI) |
|---|---|---|---|---|
| | | | | (.91-.95) |
| 2016 | | | | .95** |
| | | | | (.93-.97) |
| 2017 | | | | .98* |
| | | | | (.96-1) |
| Region (Northeast) | | | | |
| North, Central, & Midwest | | | | 1.21 |
| | | | | (1.18-1.25) |
| South | | | | 1.21 |
| | | | | (1.18-1.24) |
| West | | | | 1.29 |
| | | | | (1.25-1.33) |

Notes. Model 1 only includes predisposing predictors. Model 2 includes predisposing and enabling predictors. Model 3 includes predisposing, enabling, and need predictors. Model 4 includes all predictors from model 3 along with the year and region variables.
Because several respondents reported more than one type of health insurance coverage, categories of health insurance are dichotomized, and no group is assigned as the reference group.
All Odds Ratios are significant at p<.001, except: ***Significant at p<.01, ** Significant at p<.05, *Non-significant

## Post Estimation Results: Single Category and Hierarchical Logistic Regression Models

So far, odds ratios, corresponding 95% confidence intervals, significant at p<.001, p<.01, and p<.05 in four types of logistic regression models are estimated and compared: single predictor models, grouped predictors, hierarchical models, and the full model. These comparisons along with the post-estimation statistics help us to measure the relative importance of the variables in association with unmet medical need.

Table 10 shows the pseudo-$R^2$, AIC, and BIC for each of the hierarchical and single category models. According to the changes in pseudo-$R^{2,}$ in both hierarchical and single group (one of the predisposing, enabling, and need group of variables) logistic regressions, the relative contributions of the variables under enabling factors category (i.e. income and health insurance) was substantially more than other categories (predisposing and need) of variables.

Comparing the full (final) model in the last column with each of the single category models shows that logistic regression with only enabling variables can contribute almost to 60% of the pseudo-$R^2$ of the full model (raise from .0904 to .1511). On the other hand, however, models with only predisposing or need variables can contribute, at most, to only 21% and 26% of the final model's pseudo-$R^2$, respectively.

Similarly, as shown for model (2), adding enabling variables to hierarchical model with predisposing variables raised the pseudo-$R^2$ value from .0315 to .1125. That is, by adding income and health insurance to the initial mode, pseudo-$R^2$ raised more than 3.5 times. However, adding need variables into the third model only contributed to approximately 33% raise in the pseudo-$R^2$ value.

Lower values of AIC and BIC indicate model improvement. Statistics are estimated by including the final person weight of the sample design. Lowest values of the AIC and BIC among the single category models belongs to the model with enabling variables as predictors of unmet medical need (model 2). Similarly, in the hierarchical models, the highest decrease in the values of AIC and BIC (562-512=50) is when the income and health insurance variables added to the previous model. All these statistics highlight the higher relative importance of the enabling factors (i.e. income and insurance) in association with unmet medical need.

*Table 10. Model Comparison Statistics in predicting unmet medical need*

| Model Comparison Statistics | Model (1) | Model (2) | Model (3) | Model (4) | Final Model |
|---|---|---|---|---|---|
| **Single Category Models** | | | | | |
| Pseudo-$R^2$ | .0315 | .0904 | .0399 | .0040 | .1511 |
| N | 289453 | 291443 | 293835 | 294701 | 286410 |
| AIC | 562 | 532 | 564 | 587 | 488 |
| BIC | 562 | 532 | 564 | 587 | 488 |
| **Hierarchical Models** | | | | | |
| Pseudo-$R^2$ | .0315 | .1125 | .1503 | .1511 | .1511 |
| N | 289453 | 286967 | 286410 | 286410 | 286410 |
| AIC | 562 | 512 | 489 | 488 | 488 |
| BIC | 562 | 512 | 489 | 488 | 488 |

Note. AIC and BIC values are presented in millions (*1,000,000).

<u>Results from Machine Learning Analysis</u>

Classification and Regression Trees (CART)

Figure 15 shows the compact results from the exploratory analysis using Classification and Regression Tree (CART). Of all cases assigned into testing data (n=181,298) 9.3% had unmet medical need. Regarding the outcome variable of unmet medical need, several predictors identified to partition the data. Health insurance coverage status was the first variable that CART identified to split the data. 28% (n=5918) of those with no health insurance coverage experienced unmet medical need. On the other hand, among those with at least one type of health insurance coverage, only 6.8% (n=10960) experienced unmet medical need. Although the absolute count of adults with unmet medical need was higher in the group with health insurance coverage, the relative count, or proportion of people with unmet medical need was higher among those without health insurance coverage.

Evaluated health status was the second most important partitioning variable. 15.1% of those with poor or fair health status had unmet medical need. On the other hand, among those with evaluated health status of good or above, only 5.6% had unmet medical need.

Moving down from the root (parent) node to internal nods, and finally, terminal nodes, show partition splitting using different variables. For example, among the leaves on the left side of the tree, after poor or fine health status, data is partitioned based on the age category. Percentage of people with unmet medical need was higher among those below 36 years old (19.27%) than among adults older than 35 years old (12.43%). On one side, existing limitation was more associated with unmet medical need among younger adults. Meanwhile, on the other side, the ratio of two or below of family income to federal poverty level was more associated with unmet medical need among the older adults.

Depending on the previous partitions on the parent (root) nodes, the most influential variable might differ from category to category. Higher differences in the percentage of cases in two child (internal or terminal) nodes from the same parent (root), indicate better partitioning. For example, the first split resulted from health insurance coverage caused formation of two nodes with the percentage difference of 21.17% (28.01-6.84). Contrary to this large difference, for example, the split based on the marital status (married or not), under the "good, fair, or poor health status" node, only resulted in 2.79% (7.47-4.68) difference in unmet medical need among these two subgroups after the split. The significant ($p<.05$) unequal distribution of outcome variable of unmet medical need in each node shows that some people, depending on the place in the node, were more likely than others to be associated with the outcome variable, and have unmet medical need.

Moving down from the root (unmet medical need) to the intermediate and terminal nodes, we can identify the high-risk U.S. adult population groups with considering the interaction among the different predictor variables. That is, the conditional probability of a given adult experiencing unmet medical need varies depending on the parent (higher) node. Contrary to the previous results from the logistic regression analyses, this notion of detecting the interaction among different predictors provides more clear insight in grouping the most vulnerable populations regarding the probability of experiencing unmet medical need. For example, two most high-risk adult groups are identified as the following:

1. Adults with no health insurance coverage.
2. Adults with insurance coverage, poor or fair health status, younger than 35 years old, with at least one existing limitation, and with no Medicaid or other public insurance coverage.

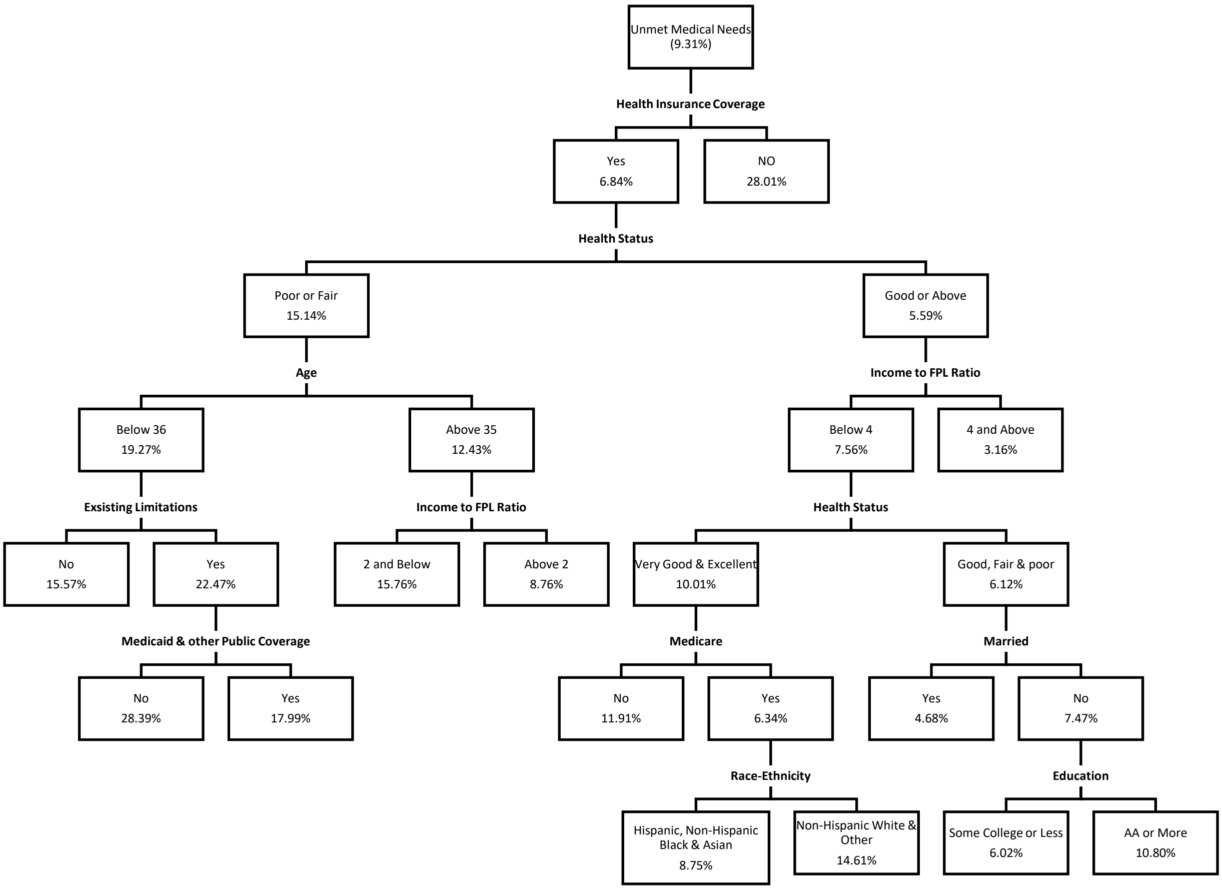


*Figure 15. Partitioning or discriminating factors for predicting unmet medical need using CART.*
Note. The value in each node is the percentage of people with reported unmet medical need in that node.

## Chi-Square Automatic Interaction Detection (CHAID)

Figure 16 shows the output from Chi-square Automatic Interaction Detection (CHAID) analysis. The outcome variable of unmet medical need is predicted using the all previous independent variables. The interpretation of the CHAID tree is similar to the CART. However, CHAID and CART vary in criteria and method used for splitting. In this case, CART partitioned based on Gini impurity, and CHAID partitioned using Chi-square test. As a result, CART only split into two extreme nodes each time. However, depending on the significance of the Chi-square test and the distribution of the variables, parent nodes in CHAID models can split into more than two child or terminal nodes.

Similar to the CART model presented in Figure 15, the first partitioning variable was lack of health insurance coverage. The data partitioned further based on the values of the categorical variable of health status. For example, among those with no health insurance coverage there was a reverse relationship between the health status and unmet medical need. That is, those with higher levels of health status (Excellent) were less likely to have unmet medical need that those with lower level of health status (i.e. poor, fair, good, and very good). For example, those with no health insurance coverage who have poor or fair health status, were more than three times more likely to have unmet medical need than those with very good or excellent health status (54% versus 17%).

Similar relationship holds true for those with health insurance coverage as well. Higher the perceived health status, lower the chances of experiencing unmet medical need. The significant unequal distribution of outcome variable of unmet medical need in each node shows that some people, depending on the place in the node, were more likely than others to be associated with the outcome variable, and have unmet medical need.

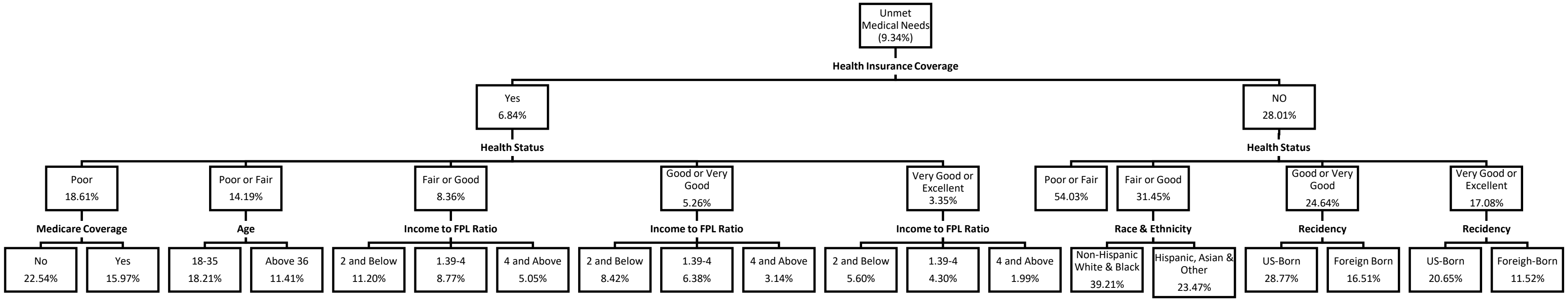


*Figure 16.* *Partitioning or discriminating factors for determining unmet medical need using CHAID (detailed output).*
Note. Only the first three rows of splits are presented here.

The relative importance of different variables is presented in Table 11 and Figure 17. Of all the 18 variables which were used in both CART and CHAID models to predict unmet medical need, only several variables exerted significant partitioning and discrimination importance in predicting unmet medical need. Hence, by knowing the value of the most important variable, no health insurance coverage in this case, we are more likely to predict correctly if a given person experiences unmet medical need or not. Better predictions can be made by using several most important variables.

Variables' importance using CART and CHAID models were similar in terms of the magnitude and order of importance. Based on the results from both models, health insurance coverage, health status, existence of limitations, and income were the most important predictors of unmet medical need.

Relative importance of no insurance coverage in predicting unmet medical need was almost 50% in both models. Health status importance was about 20% and 30% in CART and CHAID models respectively. Several variables such as marital status, Medicaid and other public health insurance coverage, and region were deemed higher important in CART than CHAID models. On the other hand, private health insurance coverage and gender were identified relatively important in CHAID than CART models.

*Table 11. Predictor Importance for unmet medical need: Results from CART and CHAID models*

| CART | | CHAID | |
|---|---|---|---|
| **Variable** | **Importance*** | **Variable** | **Importance** |
| No health Insurance | .4928 | No health Insurance | .4732 |
| Health Status | .2148 | Health Status | .2942 |
| Limitations | .0839 | Income to poverty ratio | .0867 |
| Income to poverty ratio | .0835 | Limitations | .039 |
| Family Structure | .0358 | Private Health Insurance | .022 |
| Age | .027 | Gender | .0202 |
| Medicare | .014 | Medicare | .0179 |
| Medicaid & other public coverage | .0084 | Age | .0168 |
| Residency | .0077 | Family Structure | .0151 |
| Region | .0077 | Residency | .008 |

Notes. * Predictor importance value ranges from zero to one. Values closer to 1 indicate higher importance.

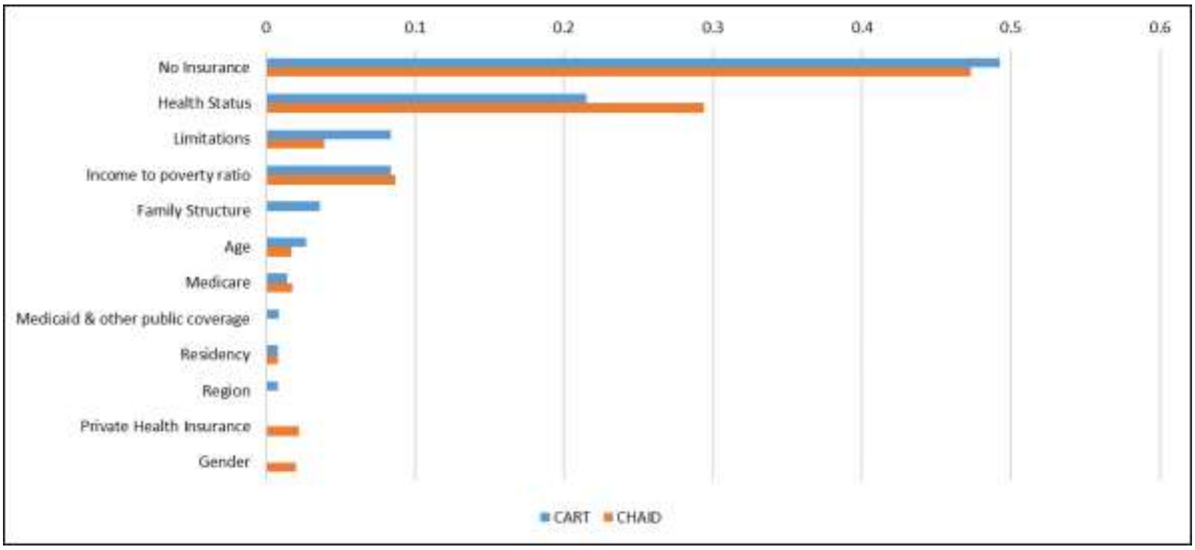


*Figure 17. Predictor Importance for unmet medical need: CART and CHAID models*

Figure 18 shows the variables' importance in predicting unmet medical need by grouping the variables under the categories of predisposing, enabling, and need variables. The importance of family structure (married or not), age, residency (U.S. born and immigration status), and gender were summed up under the predisposing factors.

Health insurance related variables and income contributed to the importance of the enabling factors. The importance of health status and existence of limitations were added together to calculate the overall importance of the need factors.

Enabling factors (health insurance and income) were more influential than predisposing and need factors.

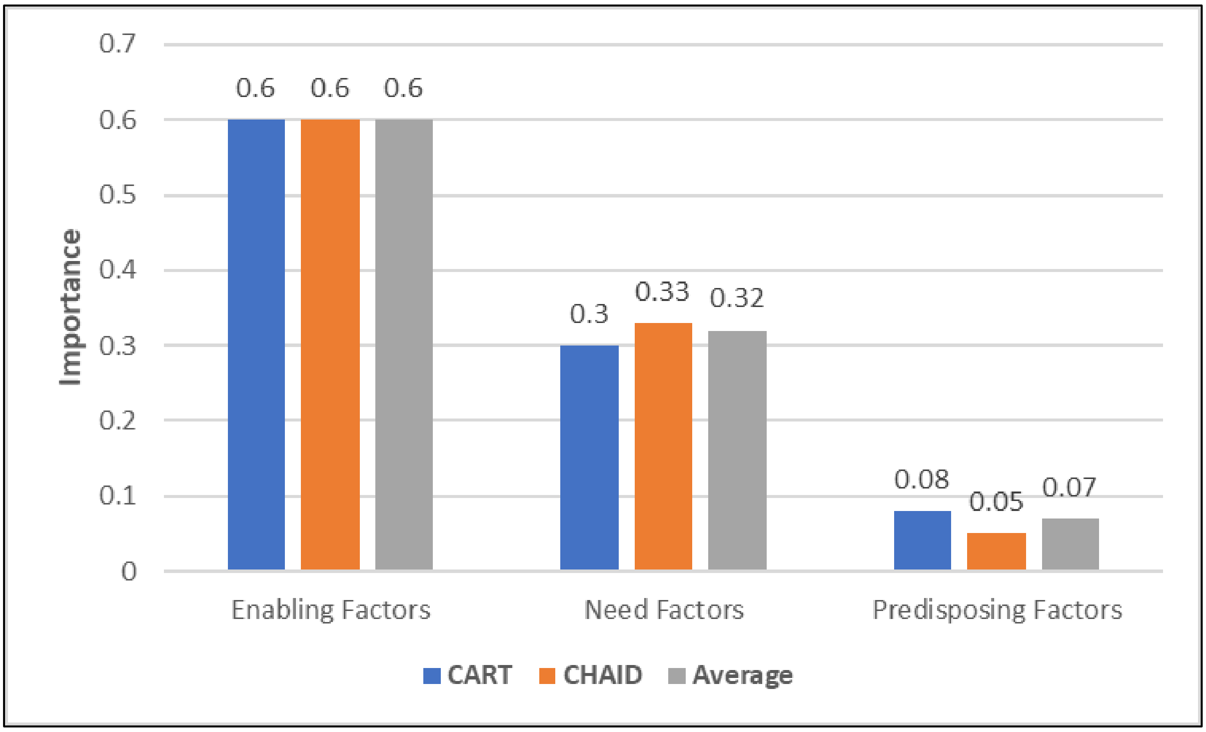


*Figure 18. Predictor importance for unmet medical need by predictor type; Results from CART and CHAID models*

Post Estimation Results: CART and CHAID Models

The confusion matrices show the percentage and frequencies of correct and wrong predictions of the dichotomous unmet medical need variable for both training and testing data in CART and CHAID models (Table 12). More than 90% of the times, both models in training and testing partitions, identified the value of the dependent variable (unmet medical need) correctly.

In both models, of the total of 284,683 cases, 70% (n=201,175) were assigned randomly to the testing partition and remaining 30% (n=86,508) were assigned to the testing partition. The models were generated using the firs 70% of the data (training phase) and then tested by fitting the other 30% of the data to generated models and comparing the predicted and actual state of having unmet medical need. In more than 90% of the cases, the value of unmet medical need was predicted correctly using both models. That is, only by knowing the values of the several variables with highest importance in predicting unmet medical need (Table 11and Figure 18), in more than 90% of the cases we can identify the risk of experiencing unmet medical need correctly.

*Table 12. Confusion Matrices: Percentage of correct predictions in CART and CHAID models*

| Partition | Training | | Testing | |
|---|---|---|---|---|
| | N | % | N | % |
| CART | | | | |
| Correct | 182,379 | 90.66% | 78,408 | 90.64% |
| Wrong | 18,796 | 9.34% | 8,100 | 9.36% |
| CHAID | | | | |
| Correct | 182,601 | 90.77% | 78,556 | 90.81% |
| Wrong | 18,574 | 9.23% | 7,952 | 9.19% |
| Agreement Between CART & CHAID | | | | |
| Agree | 198,423 | 98.63% | 85,334 | 98.64% |
| Disagree | 2,752 | 1.37% | 1,174 | 1.36% |
| Total | 201,175 | | 86,508 | |
| Agreement with Outcome | | | | |
| Correct | 181,114 | 91.28% | 77,895 | 91.28% |
| Wrong | 17,309 | 8.72% | 7,439 | 8.72% |
| Total | 198,423 | | 85,334 | |

Figure 19 shows the lift charts for comparing the prediction of unmet medical need in the sample by using CART or CHAID models versus not using these models. It determines the ratio between the results predicted by the models and the result using no model. For example, to identify people with unmet medical need, by knowing the important variables' (Table 11 and Figure 17) values and using CART or CHAID models we are between three to six times more likely to identify high-risk individuals only by selecting first decile of the total U.S. adult population.

Figure 20 shows another chart that can be used to compare the efficiency of the models. Cumulative gain chart compares the results gained by using the model versus the baseline model, and the best models. The interpretation of gain charts is relatively straight forward and similar to lift charts. The baseline indicates that, for example, for identifying 10% of people with unmet medical need, we need to ask the question from 10% of the total population. Similarly, to identify 50% of those with unmet medical need, 50% of the population should answer to the question. However, by using the CART or CHAID models and knowing the values of the most important predictors, we can estimate and target, for example, 80% of the population with unmet medical need only by identifying 40% of high-risk population. That is, identification of high-risk population is more effective using these models than relying on population mean.

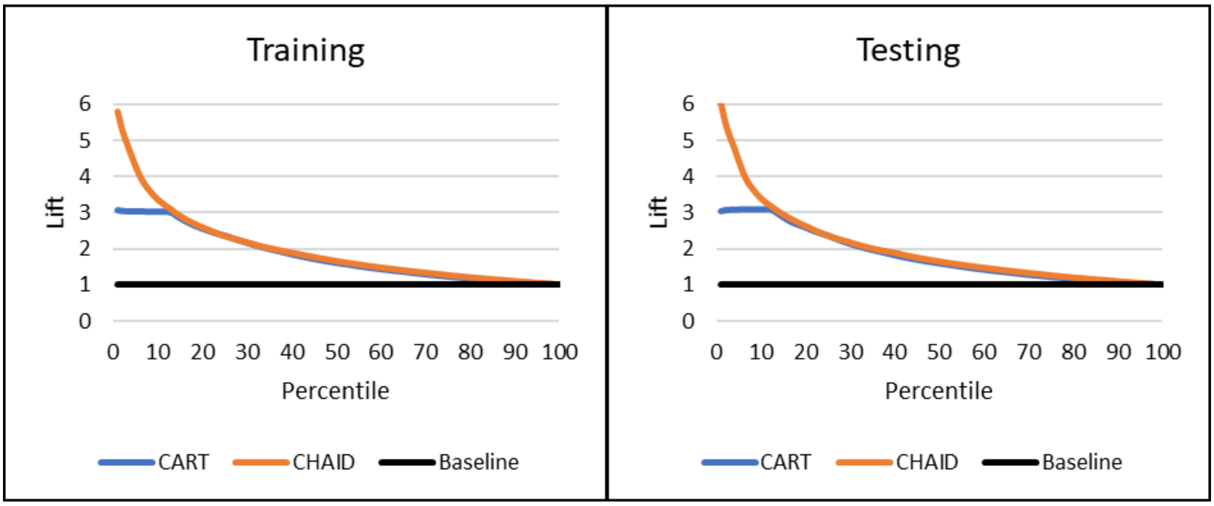


*Figure 19. Lift Charts for training and testing CART and CHAID models*

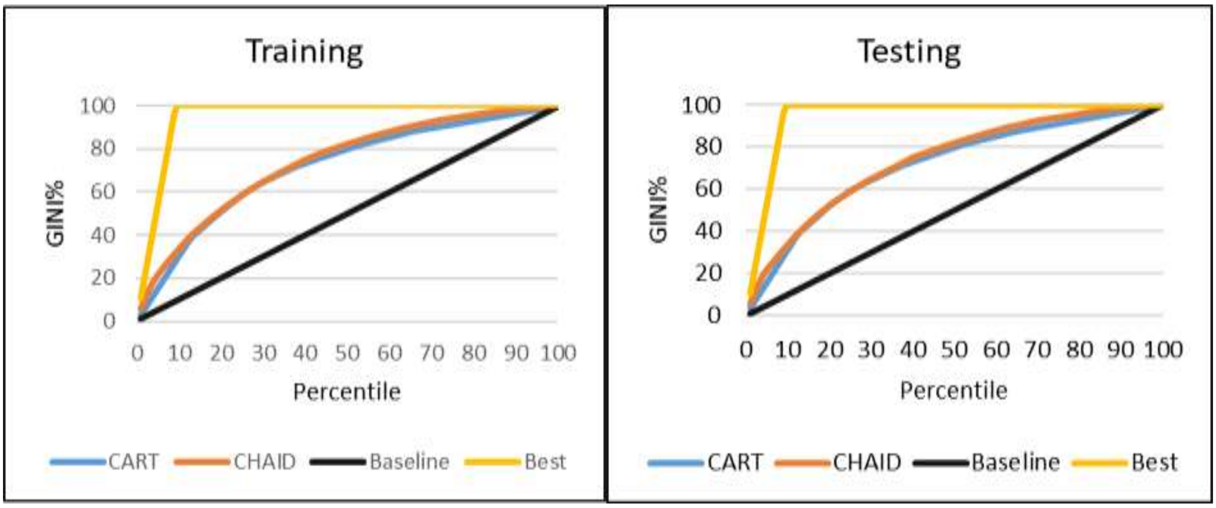


*Figure 20. Cumulative Gain Charts for training and testing CART and CHAID models*

## Conclusions of Hypothesis Testing

The two main hypotheses were tested using logistic regression, CART, and CHAID models and both were supported. That is, the null hypotheses of equal predictive power of predisposing, enabling, need factors is rejected. Similarly, the null hypothesis of equal probability of experiencing unmet medical need among different groups of adult populations is also rejected.

H_1: Enabling factors predict unmet medical need more than predisposing and need factors.

H_2: Group of population differ significantly in terms of the risk of experiencing unmet medical needs.

Additionally, several other sub-hypotheses were tested. Comprehensive list of results (compared to the initial alternative hypothesis) is presented in Table 13.

*Table 13. Hypothesis testing summary*

| Hypothesis | Supported | Not Supported |
|---|---|---|
| **Main Hypotheses** | | |
| H1A: Enabling factors predict unmet medical need more than predisposing and need factors. | X | |
| H1B: Groups of population differ significantly in terms of the risk of experiencing unmet medical needs. | X | |
| **Supplementary Hypotheses** | | |
| H1a: Female adults are more likely to have unmet medical need. | X | |
| H1b: Old Adults are more likely to have unmet medical need than middle-aged and young adults. | | X |
| H1c: Adults with higher educational attainment are less likely to have unmet medical need. | X | |
| H1d: Compared to their divorced, separated or single counterparts, married adults are less likely to have unmet medical need. | X | |
| H1e: Minority ethnoracial adults are more likely to have unmet medical need than their White counterparts. | | X |
| H1f: Immigrant adults are more likely to report unmet medical need than those born in the United States. | | X |
| H1g: Adults with higher family income to Federal Poverty Levels ratios are less likely to report unmet medical need. | X | |
| H1h: Adults with no health insurance coverage are more likely to have unmet medical need than those with at least one type of coverage. | X | |
| H1i: adults with any health-related limitations are more likely to have unmet medical need. | X | |
| H1j: adults with a history of hospitalization are more likely to report unmet medical need. | | X |
| H1k: Poor health status is associated with higher chances of experiencing unmet medical need. | X | |

Note. Results are mainly based on the hierarchical and full model from the regression analysis, CART, and CHAID models (See Table 9 for more details.)

# CHAPTER FIVE: DISCUSSION

## Discussion of Findings

The aim of this study was to estimate the relative importance of the three categories of predisposing, enabling, and need variables in association with unmet medical need. Measuring the relative importance of these three groups of variables using a pooled nationally representative sample of noninstitutionalized U.S. adults provides an understanding of the existence and the extent of health disparities and inequities in access to health care services.

The main thesis of this study was based on the conceptualization of the proportionate unmet medical need. That is, in an optimal scenario, which there is no disparities, one can expect to see unmet medical need proportionate to need for care. Those with more need for care are more likely to experience unmet medical need than those with less need for care. In other words, statistically speaking, in the case of disparities in access to health care services, the substantial amount of variation in unmet medical need is expected to be explained by predisposing or enabling factors than perceived or clinical need for medical care.

Logistic regression models along with CART and CHAID analytical approaches were implemented to test the hypotheses. Results from the three analysis methods highlight the highest importance of the enabling factors in predicting unmet medical need among U.S. adults. Additionally, results show that different groups of the U.S. adult population are not equally likely to experience unmet medical need. Hence, several vulnerable groups are, disproportionately, negatively impacted by disparities in access to medical care. That is, disparities in access to medical care, or health care in general, exist in the U.S. and deserve more attention in federal, state, and local health-related policies and programs.

## Predisposing Variables

Gender, age, highest level of educational attainment, family structure, race-ethnicity, and residency status were grouped under predisposing variables. According to the findings of this study, adult females were more likely than their male counterparts to experience unmet medical need. The relationship between gender and unmet medical need is inconsistent in the literature. These differences can be attributed to the differences in various elements such as the population and the types of the medical or mental need. For example, contrary to the findings of this study, in a study by Bryant et al. (2009), Canadian women were more likely to have unmet medical need. However, in another study using data from the National Survey on Drug Use and Health, U.S. male adults were more likely to experience unmet need for mental health care (Ojeda & Bergstresser, 2008).

Middle-aged (36-55 year old) adults were, significantly, more likely to undergo unmet medical need than young (18-35 year old) and old (55 years and older) adults. Findings from this study are consistent with the findings by Roll et al. (2013) and Ojeda and Bergstresser (2008). The association between educational attainment and unmet medical need is interesting. In the initial logistic regression models, which only included predisposing variables, adults with higher levels of education were shown to be less likely to have unmet medical need. However, surprisingly, after including income and health insurance coverage in consecutive logistic regression models, the direction of the relationship changed, and higher educational attainment was associated with more chances of unmet medical need. It seems that higher levels of education impacted unmet medical need, mainly, through better paid occupations and (or) better health insurance coverages (Atkinson & Bourguignon, 2014). Among the adults with different family structures, those who were currently married were significantly less likely to have unmet medical need than other groups of adults who were separated, divorced, widowed, living with a partner, or never married. This difference can be potentially explained, among other reasons, by more access to caregiving and emotional support among married couples or lower rate of high-risk health threatening behaviors (Lillard & Panis, 1996; Waite, 1995).

Surprisingly, in general, ethno-racial minority adults were significantly less likely to have unmet medical need, compared to White adults. Also, unexpectedly, foreign-born adults, although not significant in all models, were less likely to have unmet medical need than those who were born in the U.S. Other studies also reported contradicting (Documét & Sharma, 2004; Z. Wu, M. J. Penning, & C. M. Schimmele, 2005) or non-significant findings (Wolinsky et al., 1989).

### Enabling Variables

The association between the family income to Federal Poverty Level (FPL) ratio and unmet medical need was as expected. Adults with higher family income to FPL were, significantly, substantially less likely to have unmet medical need than those who were living in poor families. As expected, those with no insurance coverage were more than five times as likely to have unmet medical need than those with at least one type of health insurance coverage. These findings were consistent with most of the results from the previous studies (Kataoka et al., 2002; Manning et al., 1987; Warfield & Gulley, 2006). Health insurance facilitates access to health care and services through increasing financial access by, in turn, decreasing out-of-pocket payments for received services (McPake et al., 2013). However, surprisingly, adults who obtained health insurance coverage through ACA's Market Exchange were more likely to have unmet medical need than those without any health insurance coverage. This can be potentially explained by the shorter insurance coverage period, lower family income, or higher prevalence of health conditions.

### Need for Care Variables

Adults with at least one physical or mental limitation, as expected, were more likely to have unmet medical need. Additionally, it is shown that those with poor health status were more likely to have unmet medical need. These findings were similar to the results from several previous studies (Bryant et al., 2009; Morris et al., 2005; Warfield & Gulley, 2006; Z. Wu et al., 2005).

### Proxies for Overall National or Regional Policies

After controlling for all the previous variables, compared to the year 2014, U.S. adults in consecutive years were slightly less likely to have unmet medical need. However, the changes in odds ratios were minimal and non-significant. Compared to those adults living in the Northeast, U.S. adults living in other geographical regions were more likely to have unmet medical need. However, inclusion of these two variables did not add to the explanatory power of the logistic regression models.

## Generalizability of the Findings

The findings from this study can be generalizable to all of the noninstitutionalized U.S. adult population for two reasons. First, the survey design and data collection process of NHIS used complex sampling design with several strata and clusters with over-sampling of populations with less-frequent characteristics to ensure the national representativeness. Second, all the descriptive and analytical statistics in this study are performed with incorporating all the complex sampling design weights using survey subpopulation data analysis approaches. Hence, both descriptive (four-year and single year estimations) and inferential (analytical models) are generalizable at the national level.

## Implications

The findings of this study underscore the importance of population health management approaches in targeting unmet medical need. Because of the limited resources, one-size-fits-all policies should be replaced with evidence-based policy-making efforts targeting high-risk populations (Wan, 2002). Several implications can be drawn from the findings of this study. Results from CART models can be used to identify and rank groups of the U.S. adult population based on the variables with the highest importance in predicting unmet medical need. The coexistence of several high-influential categories of variables call for more attention in health-related national or federal policy making. For example, adults who have no health insurance coverage, live in families below the federal poverty level, have poor health status, and have at least one mental or physical limitation are dramatically more likely than other groups of the adult population to be negatively affected by the disparities in access to health care services. This can help to direct resources towards the areas with more return of investment in targeting health inequities.

Because of the highest importance of enabling factors, especially health insurance coverage, in predicting unmet medical need, federal, state, and local governments and non-profit agencies should focus on preparing adults with better job-market skills. Additionally, they should focus on the economic development of neighborhoods by providing incentives to investors to generate job opportunities for adults. Having better paid jobs is expected to increase income and insurance coverage and decrease disparities in access to health care services. Additionally, federal initiatives such as ACA, which aimed to increase access to health care for vulnerable populations, should be implemented properly to decrease the gap between rich and poor in access to health care services and health status.

Universal health insurance coverage can help to mitigate the disparities in access to health services and unmet medical need. However, implementation of these policies has several inherent complexities. Because of the inherent issues with the selective insurance plans, such as moral hazard on the insured side and cream skimming or cherry picking on the insurer side, risk-pooling and mandatory enrollments might be considered for long-term success of the initiatives.

Perceived health status was the second most important variable in predicting unmet medical need. Considering the higher costs associated with specialized hospitalizations, identification of adults with poorer perceived health in every encounter with the health care providers and focusing on lifestyle enrichment educations and providing preventative and screening services can improve the overall health of the adults by emphasizing on cost-benefit approaches.

## Contributions to Literature

This study contributes to the literature in several ways. For example, four-year national estimates and trends for the unmet medical need and the predictor variables, such as percentage of U.S. adults with no insurance coverage, below the federal poverty level, with poor health status, or with other characteristics, provides an overview of the issues that can be the focus of future studies.

Additionally, quantifying the relative importance of predisposing, enabling, and need factors from the Anderson’s behavioral model provides a framework to identify the most influential variables that need further attention in studying the success of national and state policies and programs.

Using alternative CART and CHAID approaches from machine learning and cross-validating findings with logistic regression models provides a successful practical implication of machine learning methods in studying health disparities and provides a framework for future researchers in studying similar research questions.

## Limitations

This study had several limitations. First, Unmet medical need was defined as a dichotomous variable and, therefore, the frequency and the magnitude of unmet medical needs are unknown. Second, respondent adults' answers to the survey questions are not contrasted with any other potential objective data such as medical, financial or employment records. Even if all respondents answered questions to the best of their knowledge, there are yet higher chances of recall bias because of the historical nature of data. Third, one adult in the household responded to all questions on behalf of all household members. The respondent's attitudes, beliefs and, knowledge may not be as the same as the other household members.

Fourth, several variables from NHIS public data files were suppressed or removed to ensure confidentiality. For example, the exclusion of the geographical variables such as county or zip-code, limited researcher in merging data from other resources such as Area Health Resource Files (AHRF), to account for availability of health services provider organizations and personnel such as hospitals and physicians per population. Finally, The NHIS does not provide any data from the health services providers to measure and control for actual service utilization or health status.

Nonetheless, to some extent, these limitations can be observed in all survey-based studies. Despite these limitations, NHIS provides a valuable source of information to study health disparities at the national level.

## Ethics and Confidentiality

The publicly available data from the NHIS repository which is used in this study, were suppressed to ensure confidentiality and eliminate the chances of reverse identification of the samples. For several variables, less frequent precise numeric values were recoded into the ranges. For example, numeric values of age for adults older than 65 were recoded into the category of 65 years old or older. Additionally, some variables were completely removed from the public data. For example, the variables of geographical residency of the person such as zip code or county was not available in the public-use files.

## Future Research

The framework and analytic methods of this study can be used to study other cases of health disparities and inequities. Access to different types of screening, diagnostic, prevention, and treatment health services can be studied by incorporating similar predictor variables in different subpopulations. For example, disparities in access to cancer screening and routine check-ups among the population that are at greater risk of specific type of cancer can be studied.

To better understand the severity and magnitude of the disparities in relation to predictor variables, future studies can focus on the frequency and severity of unmet medical need or different mental or physical health conditions by comparing the subgroups of populations such as different income or age groups.

To ensure the causal relationship between the predictors and the dependent variable of the interest, it is essential to use longitudinal panel data for the future studies of disparities in access to different types of health care services and inequities in health conditions and outcomes.

Finally, merging the data from national surveys with the neighborhood level data which include the distribution of the different types of health care providers (such as AHRF), neighborhood safety (such as U.S. News Ranking of neighborhoods), or neighborhood developmental level (such as Rural-Urban Continuum Codes by the U.S. Department of Agriculture) and analyzing the impact of neighborhood-level variables in multi-level models can highlight the role of the residential place on health status and health disparities.

# Conclusion

The main objective of this study was to assess the disparities in unmet medical need by estimating the relative importance of the predisposing, enabling, and need factors of the Anderson's behavioral model in association with unmet medical need. This study provides the four-year (2014-2017) national estimations and trends of different characteristics of the U.S. adult population. Results from the logistic regression, CART, and CHAID models indicate the existence of disparities in unmet medical need among U.S. adults. Additionally, findings show that enabling factors, including lack of health insurance converge and poverty are the more important than predisposing and need variables in predicting unmet medical need in the nationally representative sample of U.S. adults.

Results can provide several policy implications in targeting health disparities, contribute to the relevant literature, and guide the conceptualization and methodological approaches of future studies.

## APPENDIX: INSTITUITONAL REVIEW BOARD APPROVAL

UNIVERSITY OF CENTRAL FLORIDA

Institutional Review Board
FWA00000351
IRB00001138
Office of Research
12201 Research Parkway Orlando, FL 32826-3246

## NOT HUMAN RESEARCH DETERMINATION

January 3, 2019

Dear Ahmad Khanijahani:

On 1/3/2019, the IRB reviewed the following protocol:

| | |
|---|---|
| Type of Review: | Initial Study |
| Title of Study: | Determinants of Unmet medical need among U.S. Adults |
| Investigator: | Ahmad Khanijahani |
| IRB ID: | STUDY00000037 |
| Funding: | None |
| Grant ID: | None |
| IND, IDE, or HDE: | None |
| Documents Reviewed: | • irb_HRP-250-FORM-RequestForNHSR, Category: IRB Protocol;<br>• HRP-251 - FORM - Faculty Advisor Review_Khanijahani_Wan signed off.docx, Category: Faculty Research Approval; |

The IRB determined that the proposed activity is not research involving human subjects as defined by DHHS and FDA regulations.

IRB review and approval by this organization is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these activities are research involving human in which the organization is engaged, please submit a new request to the IRB for a determination. You can create a modification by clicking **Create Modification / CR** within the study.

If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu. Please include your project title and IRB number in all correspondence with this office.

Sincerely,

Racine Jacques
Designated Reviewer

## REFERENCES


Aber, J. L., Jones, S., & Cohen, J. (2000). The impact of poverty on the mental health and development of very young children.

Adamson, J., Ben-Shlomo, Y., Chaturvedi, N., & Donovan, J. (2003). Ethnicity, socio-economic position and gender—do they affect reported health—care seeking behaviour? *Social Science and Medicine*, *57*(5), 895-904. doi:10.1016/s0277-9536(02)00458-6

Allin, S., Grignon, M., & Le Grand, J. (2010). Subjective unmet need and utilization of health care services in Canada: What are the equity implications? *Social Science and Medicine*, *70*(3), 465-472. doi:http://dx.doi.org/10.1016/j.socscimed.2009.10.027

Andersen, R. (1968). A behavioral model of families' use of health services. *A behavioral model of families' use of health services.*(25).

Andersen, R., & Newman, J. F. (1973). Societal and individual determinants of medical care utilization in the United States. *Milbank Memorial Fund Quarterly: Health and Society*, *51*(1), 95-124.

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

Andersen, R. M., Yu, H., Wyn, R., Davidson, P. L., Brown, E. R., & Teleki, S. (2002). Access to medical care for low-income persons: how do communities make a difference? *Medical Care Research and Review*, *59*(4), 384-411.

Anderson, R. L., & Gittler, J. (2005). Unmet need for community-based mental health and substance use treatment among rural adolescents. *Community Mental Health Journal, 41*(1), 35-49. doi:DOI 10.1007/s10597-005-2598-0

Atkinson, A. B., & Bourguignon, F. (2014). *Handbook of income distribution* (Vol. 2): Elsevier.

Ayanian, J. Z., Weissman, J. S., Schneider, E. C., Ginsburg, J. A., & Zaslavsky, A. M. (2000). Unmet health needs of uninsured adults in the united states. *JAMA, 284*(16), 2061-2069. doi:10.1001/jama.284.16.2061

Barford, A., Dorling, D., Smith, G. D., & Shaw, M. (2006). Life expectancy: women now on top everywhere - During 2006, even in the poorest countries, women can expect to outlive men. *Bmj-British Medical Journal, 332*(7545), 808-808. doi:DOI 10.1136/bmj.332.7545.808

Bass, D. M., Looman, W. J., & Ehrlich, P. (1992). Predicting the Volume of Health and Social-Services - Integrating Cognitive Impairment into the Modified Andersen Framework. *Gerontologist, 32*(1), 33-43. doi:DOI 10.1093/geront/32.1.33

Blackwell, D. L., Martinez, M. E., Gentleman, J. F., Sanmartin, C., & Berthelot, J. M. (2009). Socioeconomic status and utilization of health care services in Canada and the United States: findings from a binational health survey. *Medical Care, 47*(11), 1136-1146. doi:10.1097/MLR.0b013e3181adcbe9

Blewett, A. L., Drew, J. A. R., Griffin, R., King, M. L., & Williams, K. C. W. (2018). IPUMS Health Surveys: National Health Interview Survey, Version 6.3. Minneapolis: University of Minnesota. In.

Bryant, T., Leaver, C., & Dunn, J. (2009). Unmet healthcare need, gender, and health inequalities in Canada. *Health Policy, 91*(1), 24-32. doi:10.1016/j.healthpol.2008.11.002

Burnham, K. P., & Anderson, D. R. (2004). Multimodel inference: understanding AIC and BIC in model selection. *Sociological methods & research, 33*(2), 261-304.

Carr, W., & Wolfe, S. (1976). Unmet Needs as Sociomedical Indicators. *International Journal of Health Services, 6*(3), 417-430. doi:Doi 10.2190/Mcg0-Uh8d-0ag8-Vfnu

CDC. (2016). *National Health Interview Survey*. Retrieved from: https://www.cdc.gov/nchs/nhis/nhis_2013_data_release.htm

CDC. (2017). NHIS Public-use data file and documentation. Retrieved January 12 2018, from National Center for Health Statistics https://www.cdc.gov/nchs/nhis/nhis_2016_data_release.htm

Chen, E., Martin, A. D., & Matthews, K. A. (2006). Understanding health disparities: The role of race and socioeconomic status in children's health. *American Journal of Public Health, 96*(4), 702-708.

Chen, L. C., Evans, T. G., & Cash, R. A. (1999). Health as a global public good. *Global public goods*, 284-304.

Chiri, G., & Warfield, M. E. (2012). Unmet need and problems accessing core health care services for children with autism spectrum disorder. *Matern Child Health J, 16*(5), 1081-1091. doi:10.1007/s10995-011-0833-6

Cochrane, S. H., OHara, D. J., & Leslie, J. (1980). The effects of education on health.

Craske, M. G., Edlund, M. J., Sullivan, G., Roy-Byrne, P., Sherbourne, C., Bystritsky, A., & Stein, M. B. (2005). Perceived unmet need for mental health treatment and barriers to care among patients with panic disorder. *Psychiatric Services, 56*(8), 988-994. doi:DOI 10.1176/appi.ps.56.8.988

Davidoff, A. J. (2004). Identifying children with special health care needs in the National Health Interview Survey: a new resource for policy analysis. *Health Services Research, 39*(1), 53-72.

Diamant, A. L., Hays, R. D., Morales, L. S., Ford, W., Calmes, D., Asch, S., . . . Gelberg, L. (2004). Delays and unmet need for health care among adult primary care patients in a restructured urban public health system. *American Journal of Public Health, 94*(5), 783-789. doi:Doi 10.2105/Ajph.94.5.783

Dicker, A. P., Ford, E. C., & Williams, T. R. (2016). *Quality and Safety in Radiation Oncology: Implementing Tools and Best Practices for Patients, Providers, and Payers*: Springer Publishing Company.

Documét, P. I., & Sharma, R. K. (2004). Latinos' health care access: financial and cultural barriers. *Journal of Immigrant Health, 6*(1), 5-13.

Doyal, L., & Gough, I. (1991). A theory of human need.

Flores, G., Abreu, M., Olivar, M., & Kastner, B. (1998). ACcess barriers to health care for latino children. *Archives of Pediatrics and Adolescent Medicine, 152*(11), 1119-1125. doi:10.1001/archpedi.152.11.1119

Flores, G., Bauchner, H., Feinstein, A. R., & Nguyen, U. S. D. T. (1999). The impact of ethnicity, family income, and parental education on children's health and use of health services. *American Journal of Public Health, 89*(7), 1066-1071. doi:Doi 10.2105/Ajph.89.7.1066

Flores, G., & Tomany-Korman, S. C. (2008). Racial and ethnic disparities in medical and dental health, access to care, and use of services in US children. *Pediatrics, 121*(2), E286-E298. doi:10.1542/peds.2007-1243

Folland, S., Goodman, A. C., & Stano, M. (2004). *The economics of health and health care* (4th ed.): Upper Saddle River, NJ : Pearson/Prentice Hall.

Frank, R. H., & Parker, I. C. (1991). *Microeconomics and behavior*: McGraw-Hill New York.

Friedman, B., & Basu, J. (2004). The rate and cost of hospital readmissions for preventable conditions. *Medical Care Research and Review, 61*(2), 225-240.

Frohlich, K. L., & Potvin, L. (2008). Transcending the known in public health practice: the inequality paradox: the population approach and vulnerable populations. *American Journal of Public Health, 98*(2), 216-221.

Garland, A. F., Lau, A. S., Yeh, M., McCabe, K. M., Hough, R. L., & Landsverk, J. A. (2005). Racial and Ethnic Differences in Utilization of Mental Health Services Among High-Risk Youths. *American Journal of Psychiatry, 162*(7), 1336-1343. doi:doi:10.1176/appi.ajp.162.7.1336

Heslin, K. C., Casey, R., Shaheen, M. A., Cardenas, F., & Baker, R. S. (2006). Racial and ethnic differences in unmet need for vision care among children with special health care needs. *Archives of Ophthalmology, 124*(6), 895-902. doi:DOI 10.1001/archopht.124.6.895

Hou, F., & Chen, J. (2002). Unmet needs for health care. *Health Reports, 13*(2), 23.

Kandrack, M. A., Grant, K. R., & Segall, A. (1991). Gender Differences in Health Related Behavior - Some Unanswered Questions. *Social Science and Medicine, 32*(5), 579-590. doi:Doi 10.1016/0277-9536(91)90293-L

Kataoka, S. H., Zhang, L., & Wells, K. B. (2002). Unmet need for mental health care among US children: Variation by ethnicity and insurance status. *American Journal of Psychiatry, 159*(9), 1548-1555. doi:DOI 10.1176/appi.ajp.159.9.1548

Lasser, K. E., Himmelstein, D. U., & Woolhandler, S. (2006). Access to care, health status, and health disparities in the United States and Canada: results of a cross-national population-based survey. *American Journal of Public Health, 96*(7), 1300-1307. doi:10.2105/AJPH.2004.059402

Lillard, L. A., & Panis, C. W. (1996). Marital status and mortality: the role of health. *Demography, 33*(3), 313-327.

Lo, K.-M., & Fulda, K. G. (2008). Impact of predisposing, enabling, and need factors in accessing preventive medical care among US children: results of the national survey of children's health. *Osteopathic Medicine and Primary Care, 2*(1), 12.

Manning, W. G., Newhouse, J. P., Duan, N., Keeler, E. B., Leibowitz, A., & Marquis, M. S. (1987). Health insurance and the demand for medical care: evidence from a randomized experiment. *American Economic Review, 77*(3), 251-277.

Mayer, M. L., Skinner, A. C., Slifkin, R. T., & National Survey of Children With Special Health Care, N. (2004). Unmet need for routine and specialty care: data from the National Survey of Children With Special Health Care Needs. *Pediatrics, 113*(2), e109-115.

McColl, M. A., Jarzynowska, A., & Shortt, S. E. D. (2010). Unmet health care needs of people with disabilities: population level evidence. *Disability & Society, 25*(2), 205-218. doi:Pii 919680307

10.1080/09687590903537406

McPake, B., Normand, C., & Smith, S. (2013). *Health economics: an international perspective*: Routledge.

Middelboe, T., Mackeprang, T., Hansson, L., Werdelin, G., Karlsson, H., Bjarnason, O., . . . Sandlund, M. (2001). The Nordic Study on schizophrenic patients living in the community. Subjective needs and perceived help. *European Psychiatry, 16*(4), 207-214.

Miranda-Castillo, C., Woods, B., Galboda, K., Oomman, S., Olojugba, C., & Orrell, M. (2010). Unmet needs, quality of life and support networks of people with dementia living at home. *Health and quality of life outcomes, 8*(1), 132. doi:Artn 132

10.1186/1477-7525-8-132

Mollborn, S., Stepanikova, I., & Cook, K. S. (2005). Delayed care and unmet needs among health care system users: when does fiduciary trust in a physician matter? *Health Services Research, 40*(6p1), 1898-1917.

Morris, S., Sutton, M., & Gravelle, H. (2005). Inequity and inequality in the use of health care in England: an empirical investigation. *Social Science and Medicine, 60*(6), 1251-1266. doi:10.1016/j.socscimed.2004.07.016

Neugarten, B. L. (1974). Age Groups in American Society and the Rise of the Young-Old. *Annals of the American Academy of Political and Social Science, 415*, 187-198. doi:10.2307/1041105

Newacheck, P. W., Hughes, D. C., Hung, Y.-Y., Wong, S., & Stoddard, J. J. (2000). The Unmet Health Needs of America's Children. *Pediatrics, 105*(Supplement 3), 989-997.

Newacheck, P. W., Hung, Y. Y., Jane Park, M., Brindis, C. D., & Irwin, C. E. (2003). Disparities in Adolescent Health and Health Care: Does Socioeconomic Status Matter? *Health Services Research, 38*(5), 1235-1252. doi:10.1111/1475-6773.00174

Ojeda, V. D., & Bergstresser, S. M. (2008). Gender, race-ethnicity, and psychosocial barriers to mental health care: An examination of perceptions and attitudes among adults reporting unmet need. *Journal of Health and Social Behavior, 49*(3), 317-334. doi:Doi 10.1177/002214650804900306

Palmer, S. J. (1993). Care of sick children by parents: a meaningful role. *Journal of Advanced Nursing, 18*(2), 185-191.

Penz, G. P. (2008). Consumer sovereignty and human interests. *Cambridge Books*.

Prentice, J. C., & Pizer, S. D. (2007). Delayed access to health care and mortality. *Health Services Research, 42*(2), 644-662.

Raftery, A. E. (1995). Bayesian model selection in social research. *Sociological Methodology*, 111-163.

Rice, T., Rosenau, P., Unruh, L. Y., Barnes, A. J., Saltman, R. B., & van Ginneken, E. (2013). Health Systems in Transition. *Health, 15*(3).

Ridley, M. (1993). *The red queen sex and the evolution of human nature*. New York: Macmillan Publishing Company.

Rivnyak, M. H., Wan, T. T. H., Stegall, M. H., Jacobs, M., & Li, S. (1989). Ambulatory Care Use among the Noninstitutionalized Elderly - a Causal Model. *Research on Aging, 11*(3), 292-311. doi:Doi 10.1177/0164027589113002

Roll, J. M., Kennedy, J., Tran, M., & Howell, D. (2013). Disparities in unmet need for mental health services in the United States, 1997–2010. *Psychiatric Services, 64*(1), 80-82.

Rothgang, H., Cacace, M., Frisina, L., Grimmeisen, S., Schmid, A., & Wendt, C. (2010). *The state and healthcare: comparing OECD countries*: Springer.

Salvatore, D. (1991). *Microeconomics / Dominick Salvatore*: New York : HarperCollins, c1991.

Sandel, M. J. (2012). *What money can't buy: the moral limits of markets*: Macmillan.

Schoenborn, C. A., Adams, P. F., & Peregoy, J. A. (2013). Health behaviors of adults: United States, 2008-2010. *Vital and health statistics. Series 10, Data from the National Health Survey*(257), 1-184.

Skinner, A. C., Slifkin, R. T., & Mayer, M. L. (2006). The effect of rural residence on dental unmet need for children with special health care needs. *Journal of Rural Health, 22*(1), 36-42. doi:10.1111/j.1748-0361.2006.00008.x

Sommers, B. D., Buchmueller, T., Decker, S. L., Carey, C., & Kronick, R. (2012). The Affordable Care Act has led to significant gains in health insurance and access to care for young adults. *Health Affairs, 32*(1), 165-174.

Stein, J. A., Andersen, R., & Gelberg, L. (2007). Applying the Gelberg-Andersen behavioral model for vulnerable populations to health services utilization in homeless women. *Journal of Health Psychology, 12*(5), 791-804. doi:10.1177/1359105307080612

Trani, J. F., & Loeb, M. (2012). Poverty and disability: a vicious circle? Evidence from Afghanistan and Zambia. *Journal of International Development*, *24*(S1).

True, W. R., Romeis, J. C., Heath, A. C., Flick, L. H., Shaw, L., Eisen, S. A., . . . Lyons, M. J. (1997). Genetic and environmental contributions to healthcare need and utilization: a twin analysis. *Health Services Research*, *32*(1), 37-53.

Tucker-Seeley, R. D., Mitchell, J. A., Shires, D. A., & Modlin, C. S. (2015). Financial Hardship, Unmet Medical Need, and Health Self-Efficacy Among African American Men. *Health Education and Behavior, 42*(3), 285-292. doi:10.1177/1090198114557125

Wagstaff, A. (2002). Poverty and health sector inequalities. *Bulletin of the World Health Organization, 80*, 97-105.

Waite, L. J. (1995). Does marriage matter? *Demography, 32*(4), 483-507.

Wan, T. T. (2002). *Evidence-based health care management: Multivariate modeling approaches*: Springer Science & Business Media.

Warfield, M. E., & Gulley, S. (2006). Unmet need and problems accessing specialty medical and related services among children with special health care needs. *Maternal and Child Health Journal*, *10*(2), 201-216. doi:10.1007/S10995-005-0041-3

Weissman, J. S., Stern, R., Fielding, S. L., & Epstein, A. M. (1991). Delayed access to health care: risk factors, reasons, and consequences. *Annals of Internal Medicine, 114*(4), 325-331.

Wells, K., Klap, R., Koike, A., & Sherbourne, C. (2001). Ethnic disparities in unmet need for alcoholism, drug abuse, and mental health care. *American Journal of Psychiatry, 158*(12), 2027-2032. doi:10.1176/appi.ajp.158.12.2027

WHO. (n.d.). The determinants of health. Retrieved from http://www.who.int/hia/evidence/doh/en/

Wolinsky, F. D., Aguirre, B. E., Fann, L. J., Keith, V. M., Arnold, C. L., Niederhauer, J. C., & Dietrich, K. (1989). Ethnic-Differences in the Demand for Physician and Hospital Utilization among Older Adults in Major American Cities - Conspicuous Evidence of Considerable Inequalities. *Milbank Quarterly, 67*(3-4), 412-449. doi:Doi 10.2307/3350222

Wolinsky, F. D., & Johnson, R. J. (1991). The Use of Health-Services by Older Adults. *Journals of Gerontology, 46*(6), S345-S357. doi:DOI 10.1093/geronj/46.6.S345

Wu, Z., Penning, M. J., & Schimmele, C. M. (2005). Immigrant status and unmet health care needs. *Canadian Journal of Public Health/Revue Canadienne de Sante'e Publique*, 369-373.