Walden University

ScholarWorks

Walden Dissertations and Doctoral Studies

Walden Dissertations and Doctoral Studies Collection

2020

Clostridium Difficile Incidence in Acute Care Hospitals: Patient and Hospital Characteristics

Angela Nwachuku
Walden University

Walden University

College of Health Sciences

This is to certify that the doctoral study by

Angela Nwachuku

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

Review Committee
Dr. Namgyal Kyulo, Committee Chairperson, Public Health Faculty
Dr. Susan Nyanzi, Committee Member, Public Health Faculty
Dr. German Gonzalez, University Reviewer, Public Health Faculty

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

Walden University
2020

Abstract

Clostridium Difficile Incidence in Acute Care Hospitals: Patient and Hospital

Characteristics

By

Angela Nwachuku

MSHCM, West Coast University 2012

BA, California State University Northridge 2011

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Public Health

Walden University

May 2020

Abstract

Hospital acquired infections (HAIs) calls for the attention of public research because it allows for investigation of the health practices, resources, and barriers of different health facilities and their surrounding communities. This research study examined the relationship between hospital acquired clostridium difficile infection (CDI) and patient, socioeconomic, and hospital characteristics in the state of New Mexico to determine their correlation with the increased incidence of CDI between 2013 and 2015 and if significant differences exist. The research questions were explored with the implication of the fundamental cause model and the pathways model. New Mexico patients over the age of 18 and admitted to an acute care facility in 2014 and 2015 (n=186,669) were examined using a case-control, correlative, retrospective approach. The relationship between the study predictors: patient, socioeconomic, and hospital characteristics, and outcome variable, presence of a CDI diagnosis, was analyzed using a test of binomial logistic regression. Females (OR=1.31), Native Americans (OR=1.51), increase in age and number of diagnoses (OR=1.14; OR< 0.00), and increase in length of stay (OR=1.14) showed an increased likelihood of a CDI diagnosis. Medicaid users (OR=-0.63), income groups in the 4th quartile (OR=0.02), and surgical patients (OR=5.70) presented a significant association with the likelihood of a CDI diagnosis. The findings of the study address the social implication of how differences in health services, health resources, and financial barriers impact CDI prevention programs and if such impacts differ greatly across New Mexico jurisdictions and communities. There is a need to ensure that all New Mexico communities have standardized protocols and resources for CDI prevention.

Clostridium Difficile Incidence in Acute Care Hospitals: Patient and Hospital Characteristics

by

Angela Nwachuku

MSHCM, West Coast University 2012

BA, California State University Northridge 2011

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Public Health

Walden University

May 2020

Dedication

First and foremost, I express my gratitude and thanks to the Lord above for the strength, knowledge, wisdom, and perseverance to develop and complete this research study. I would like to dedicate this manuscript to my family: Goldie (mother), Okey (father), David (brother), Daniel (brother), and Christine (sister). In addition, I would also like to extend this dedication to a few very special friends: Cory Clark, Alexander Clark, Vanesa Collis, Sally Comer, and Pelavi Mandalia. Without the support and encouragement from these individuals, the journey to the completion of this research project would not have been possible. For that, I am truly grateful.

Acknowledgments

I would like to recognize with deepest gratitude the invaluable assistance, counsel, encouragement, and expertise that Dr. Namgyal Kyulo provided during my dissertation journey. It is whole-heartedly appreciated that his steadfast guidance as my chair for my study proved monumental towards that success of this research project. I would also like to express my appreciation to committee members Dr. Jeff Snodgrass and Dr. Susan Nyanzi; URR, Dr. German Gonzalez, and statistics mentor, Dr. Zin Htway. Finally, I would like to extend my appreciation to all the peers and individuals who had a role in making this dissertation journey possible. Thank you to each and every one of you for helping me to become an independent and professional scholar and practitioner in the scientific and academic community. I look forward to utilizing this newly acquired subject-matter expertise and knowledge to contribute to improving the health and well-being of individuals and communities around the globe.

Table of Contents

List of Tables v

Section 1: Foundation of the Study and Literature Review 1

Background/Significance 3

Problem Statement 4

Antimicrobial Stewardship and Antibiotic Prescribing Practices 5

Aging Population 6

Length of Stay.. 7

Readmission Rates 7

Purpose of Study 8

Research Questions 9

Conceptual Framework 10

The Fundamental Cause Model 10

The Pathways Model.. 11

Nature of Study 12

Definitions..13

Key Terms... 13

Independent Variables 15

Dependent Variables 16

Assumptions...16

Scope and Delimitations 17

Literature Search Strategy 17

Inclusion Criteria 18

Exclusion Criteria 19

Literature Review..19

Socioeconomic Characteristics 19

Hospital Service Lines 22

Hospital Teaching Status 25

Other Factors Associated with CDI Risk 26

Patient Characteristics and CDI Risk... 31

Social Change Implications 33

Section 2: Research Design and Data Collection 35

Purpose of Study 35

Research Design..35

Variables of Interest 35

Data Collection Source and Procedure 36

Study Population and Participants 38

New Mexico Population Characteristics 38

Target Population 42

Sampling Design 43

Study Participants and Sampling Frame 43

Sample Size 44

Instrumentation and Operationalization..45

Instrumentation of Constructs 45

Operationalization of Constructs, Independent Variables 47

Operationalization of Constructs, Dependent Variables 50

Data Analysis Plan 51

Restatement of the Research Hypotheses 51

Threats to Validity 54

Internal Threats to Validity 54

External Threats to Validity 55

Construct Threats to Validity 55

Ethical Considerations 56

Section 3: Presentation of the Results and Findings 58

Introduction 58

Data Collection of Secondary Data 58

Data Collection Source 58

Inferential Statistics 59

Confounders 62

Analysis of Hypotheses 63

Research Question 1 63

Research Question 2 71

Research Question 3 76

Conclusion 78

Section 4: Application to Professional Practice and Implication for Social Change 80

Discussion 80

Key Findings....80

Patient Characteristics.... 80

Socioeconomic Characteristics.... 84

Hospital Characteristics.... 85

Alignment with the Theoretical Framework....86

Limitations....88

Recommendations for Further Research....89

Implications for Professional Practice and Social Change....90

Conclusion....90

References....92

List of Tables

Table 1. Table of Income Ranges for Annual Median Household Income 49

Table 2. Descriptive Characteristics for Continuous Variables....................................... 60

Table 3. Descriptive Characteristics for Categorical Variables....................................... 61

Table 4. Binary Logistic Regression for Gender 64

Table 5. Binary Logistic Regression for Gender, Adjusted with Covariates.................... 65

Table 6. Binary Logistic Regression for Age Group 66

Table 7. Binary Logistic Regression for Race 67

Table 8. Binary Logistic Regression for Number of Diagnoses (Grouped) 68

Table 9. Binary Logistic Regression for Number of Diagnoses (Grouped), Adjusted with Covariates 69

Table 10. Binary Logistic Regression for Length of Stay 70

Table 11. Binary Logistic Regression for Length of Stay, Adjusted with Covariates...... 71

Table 12. Binary Logistic Regression for Payer Type... 73

Table 13. Binary Logistic Regression for Payer Type, Adjusted with Covariates 74

Table 14. Binary Logistic Regression for Median Household Income Quartiles............ 75

Table 15. Binary Logistic Regression for Median Household Income Quartiles, Adjusted with Covariates 76

Table 16. Binary Logistic Regression for Hospital Service Line 77

Table 17. Binary Logistic Regression for Hospital Service Line, Adjusted with Covariates 78

Section 1: Foundation of the Study and Literature Review

Hospital acquired infections (HAIs) have been at the forefront of many public health initiatives and research efforts for several decades (Al-Tawfig & Tambyah, 2014). In the United States, HAIs continue to present a burden to patient safety, hospital costs, and hospital quality of care (Zimlichman et al., 2015). Several public health policies and programs have been developed to investigate causes of HAIs and to monitor healthcare practices in HAI prevention. Safdar et al. (2014) mention organizations, such as the Society for Healthcare Epidemiology, that have drafted white papers to address the need for further research and guidelines to investigate the origins and outcomes of HAI prevalence. The National and State-Specific Healthcare-Associated Infections (HAI) progress report is another public health policy-driven surveillance system developed by the National Healthcare Safety Network (NHSN) (Herzig, Reagan, Pogorzelska-Maziarz, Srinath, & Stone, 2014). The HAI Progress Report provides summaries of incidence trends and intervention goals across a number of healthcare facilities for the following HAIs: central line-associated bloodstream infections, catheter-associated urinary tract infections, ventilator-associated pneumonia, surgical site infections, clostridium difficile infections (CDIs), methicillin-resistant staphylococcus aureus, and vancomycin-resistant enterococci (Herzig et al., 2014). Among these HAIs, CDI is the most precarious under public health surveillance (Fischer et l., 2016; Leffler & Lamont, 2015).

CDI is a bacterial infection of the colon that disrupts the production, population, and functioning of the colon’s normal flora (Ghose, 2013; Tung, Lopez, Orenstein, & Novitsky, 2017). Disruption of the body’s normal flora and overproduction of clostridium difficile results in multiple enteric complications such as inflammation of the colon and diarrhea (Ghose, 2013). A patient can develop CDI in the hospital or in the community from prolonged antibiotic use, contact with an infected person or agent, or both (Ghose, 2013). Untreated or undiagnosed CDI increases the risk of mortality (Ghose, 2013; Tung et al., 2017). In the last decade, CDI accounted for more than 500,000 infections, 9% of hospital deaths, and more than $400 million in economic burden (Napolitano & Edmiston, 2017).

The Emerging Infections Program (EIP) was developed by the Centers for Disease Control and Prevention (CDC) to address the problem of CDI and other HAI incidences in select hospitals with the goal of mitigating the problem of incidence by a desired timeframe and under specific surveillance objectives (Hadler et al., 2015). The EIP, a national surveillance program, addresses infectious disease risks thought the strategic integration of different health departments, academic institutions, federal organizations, and local government programs (Hadler et al., 2015). The EIP's objectives and goals for CDI are specific to facility types and hospital region (Hadler et al., 2015). Approximately 10 states are under the EIP program for CDI (Chitnis et al., 2013; Guh et al., 2017). New Mexico is one of the states participating in the EIP (Magill et al., 2017), with the greatest increase in standard infection ratios (SIR) between 2013 and 2015 compared to other states.

The New Mexico EIP program, with surveillance efforts occurring in Bernalillo County, focuses on acute care facilities, long-term care facilities, nursing homes, and rehabilitation centers despite the different protocols used to measure, test, and report CDI incidence. Recent studies have investigated the epidemiology of CDI in New Mexico and other acute care hospitals across the nation by observing hospital size, hospital type, antimicrobial stewardship, patient demographics, and other hospital characteristics to explain the high incidence rate (Dudeck et al., 2013; Magill et al., 2014). However, there is limited research on the characteristics of the New Mexico acute care facilities under surveillance with regard to commonly used insurance and income groups as the reported CDI SIRs for New Mexico include information on the state's socioeconomic characteristics. A state's socioeconomic characteristics can provide information on the patient demographic, average cost of care, access to health resources, insurance use, and needs of the population (Arpey, Gaglioti, & Rosenbaum, 2017). This is valuable for public health researchers when observing health trends and determining if certain health disparities exist based on socioeconomic characteristics of a healthcare service area (Bravemen, 2014); especially with regard to HAI prevalence patterns (Dubberke et al., 2014).

Background/Significance

The rise in CDI, especially in New Mexico, has prompted research efforts by multiple stakeholders and public health research practitioners (DePestel & Aronoff, 2013; Lessa et al., 2014; Lessa et al.; 2015). Current research efforts focus on initiatives such as antimicrobial stewardship (Calfee, 2012) and hand hygiene compliance programs (Fayerberg, Bouchard, & Kellie, 2013; Jullian-Desayese, Landelle, Mallaret, Brun-Buisson, & Barbut, 2017) and risk factors such as existing comorbidities upon admission (Bloomfield & Riley, 2016; Miller, Polgreen, Chavanaugh, & Polgreen, 2016) as observable variables associated with CDI. Other factors such as hospital length of stay (Miller, 2015; Miller et al., 2016) and number of beds (Fayerberg et al., 2013; Schechner, Carmeli, & Leshno, 2017) have also been studied to determine their relationship with CDI incidence.

Although studies have presented findings on the increase in observed CDI cases versus predicted cases in multiple New Mexico counties between 2013 and 2015 (CDC 2015; CDC, 2016), differences in SIRs and CDI prevalence among different insurance and income groups across New Mexico, and their association with patient characteristics and sociodemographic factors, have not been explored. In respect to social change, the findings from this study can prompt investigation and reassessment of CDI management behaviors, standard precaution practices, and management policies standard across all acute care hospitals and serve to decrease CDI incidence, particularly among socioeconomic groups that present high SIRs and CDI incidence. It will also serve to determine if the association between the variables presents a social and geographic disparity in CDI management.

Problem Statement

CDI is the leading HAI in the United States with 94% of reported HAI originating from CDI incidence (Evans & Safdar, 2015). According to Lessa et al. (2015), CDI accounted for more than 500,000 HAI cases and 29,000 reported deaths in the United States in 2011. The rate of hospital-acquired CDI is 2.8 to 9.3 per 10,000 patient-days (Evans & Safdar, 2015). The average mortality rate for CDI is 14,000 deaths per year, with 90% deaths occurring in populations over the age of 65 years (Evans & Safdar, 2015). Hospital length of stay, frequent antibiotic use, and age are the greatest risk factors for CDI exposure and acquisition (Evans & Safdar, 2015; Lessa et al., 2015). This will be discussed in greater detail in the following sections.

According to the 2015 and 2016 HAI progress reports, the 2014 and 2015 SIR for CDI in New Mexico is above the national baseline (CDC, 2015; CDC, 2016). The percentage increase in SIRs indicates that the state is experiencing increases in observed CDI incidence above the predicted national average (CDC, 2015; CDC, 2016). CDI in New Mexico had an SIR of 1.04 in 2013, which is not statistically significant compared to the national SIR of 0.90. This is due in part to the unavailability of data from 2012 to compare and observe trends (CDC, 2014). However, for 2014 and 2015, New Mexico exhibited increased SIRs of 1.14 and 1.32, respectively (CDC, 2015; CDC, 2016). This is in contrast with the national SIRs of 0.92 and 0.998 for the same years (CDC. 2015; CDC, 2016). The SIRs in 2014 and 2015 for New Mexico indicate that the state is doing worse than the national baseline; the state is experiencing a significant increase in the number of reported CDI cases—more than what has been predicted (CDC, 2015; CDC, 2016). The following sections provide some insight on the possible causes or factors that influence CDI incidence in New Mexico hospitals.

Antimicrobial Stewardship and Antibiotic Prescribing Practices

Literature on CDI incidence rates present some hypotheses and observations on the factors that influence reported CDI cases. One example is evident in a study by Ross et al. (2015) in which the protocol for antimicrobial stewardship and infectious disease prevention was observed in a New Mexico university teaching hospital. They found that nonaudited antimicrobials and improper prescribing of antibiotics impacted hospital costs (Ross et al., 2015). The patients who received audited antimicrobial treatment and properly prescribed antibiotics had shorter patient-days (length of stay) and were less likely to develop CDI (Bui et al., 2016).

Conversely, changes in antimicrobial stewardship programs in 14 California acute care hospitals during a 1-year study period (2010–2011) showed little impact on CDI incidence reduction based on Yui et al.'s (2014) findings. However, this could be due in part to a change in diagnostic protocol and instrumentation during the 1-year study period (Yu et al., 2014). Nonetheless, Yui et al. (2014) provided some evidence that antimicrobial stewardship has an influence on CDI rates in California acute care facilities. Dantes et al. (2015) suggested that reduction in the prescribing of antibiotics could significantly lower community-acquired CDI; this could provide insight on modification of the antibiotic-prescribing practices for CDI at the hospital level.

Aging Population

The increase of the geriatric population can influence the rise in CDI rates (Abdullatif & Noymer, 2016). One of the most notable characteristics associated with CDI risks is age. Individuals over the age of 65 have a significantly higher risk of developing CDI compared to other age groups (Abdullartiff & Noymer, 2016; Pechal, Lin, Allen, & Reveles, 2016; Ziakas et al., 2016). Age was also associated with increased antibiotic-prescribing practices (Dantes et al., 2015; Hunter et al., 2015) which, as mentioned in the preceding section, inversely increases CDI risk. Hunter et al. (2015) explore the relationship between increased CDI rates and patients over 65 years of age in

New Mexico nursing care facilities as well as that of the other 10 participating EIP states. Their findings indicate that CDI rate and age showed a strong correlation.

Length of Stay

Safdar et al. (2015) mentioned that longer length of stay was a risk factor for developing CDI. In a study by Miller et al. (2016), increase in length of stay increased with age, thus increasing risk of CDI development.

Readmission Rates

Although not directly a cause of CDI development, readmission rates have been noted to have a strong association with CDI incidence risks. According to Horton et al. (2014), Gohil et al. (2015), and Tapper, Halbert, and Mellinger (2016), individuals diagnosed with HAIs such as CDI have a higher likelihood of being readmitted to a hospital. Readmission increases the prevalence of CDI in a healthcare setting; either by reacquisition of the pathogen or transmitting the pathogen to others. This is a quality indicator issue as it makes a hospital more susceptible to hospital-acquired CDI (Gohil et al., 2015; Halbert et al., 2016), raising costs (Gohil et al., 2015; Halbert et al., 2016), and raising morbidity and mortality rates (Gohil et al., 2015).

Gohil et al. (2015) explored the correlation between readmission rates and hospital risk factors in 323 California acute care hospitals between 2009 and 2011. The outcomes of the study showed that 30% of all readmission in the 323 acute care facilities were associated with HAIs and other related factors, including CDI. Horton et al. (2014) found that patients in the California Cedars Sinai Medical Center with inflammatory bowel disease had high rates of readmission due to CDI in a 2006–2010 retrospective study. Of the 5,120 subjects hospitalized, 114 had inflammatory bowel disease and CDI (Horton et al., 2014). Of these patients, there was a 24% readmission rate (Horton et al., 2014). These studies, and others, suggest the reduction of hospital readmission rates through intervention strategies can help mitigate the risk of CDI exposure (Tapper et al., 2016).

Factors such as socioeconomic characteristics, hospital characteristics such as service lines, and associated patient demographics have yet to be observable and measurable influences on CDI incidence in New Mexico acute care hospitals. Socioeconomic groups in one income pool may have different resources and services for CDI prevention and management than groups in another income pool. Socioeconomic groups may also indicate differences in frequently used insurance payer groups for different hospitals, population size, and admission and readmission rates of hospitals, which may have an association with CDI risks. Investigating socioeconomic and patient characteristics will provide an opportunity to identify whether CDI incidence patterns throughout New Mexico acute care facilities share common characteristics based on these variables.

Purpose of Study

The purpose of this study was to explore the relationship between CDI incidences in New Mexico acute care facilities with regard to hospital characteristics and patient characteristics. The incidence was expressed through the presence of a diagnosis. The independent variables of this study include: New Mexico acute care and community facilities, hospital characteristics (service lines), and patient demographic information.

The dependent variables include reported CDI cases across facilities. In this study, I used a quantitative approach to analyze the variables of interest. I examined whether New Mexico sociodemographic variables and acute care hospital location and characteristics had a significant association with the number of diagnosed CDI cases.

Research Questions and Hypotheses

RQ1: What is the association between patient characteristics (gender, age, race, number of diagnoses, length of stay) and hospital-acquired CDI diagnoses?

$H_0$1: There is no significant association between patient characteristics and CDI diagnoses.

H_a1: There is a significant association between patient characteristics and CDI diagnoses.

RQ2: What is the association between socioeconomic characteristics (insurance type and income group) and hospital-acquired CDI diagnoses?

$H_0$2: Socioeconomic characteristics have no significant association with CDI diagnoses.

H_a2: Socioeconomic characteristics have a significant association with CDI diagnoses.

RQ3: What is the association between acute care hospitals characteristics (service lines) and hospital-acquired CDI diagnoses?

$H_0$3: Acute care hospital characteristics have no significant association with CDI diagnoses.

H_a3: Acute care hospital characteristics have a significant association with CDI diagnoses.

Conceptual Framework

This study was grounded on two different conceptual models of health and health behavior: the fundamental cause model (Phelan, Link, & Tehranifar, 2010; Diez Roux, 2012) and the pathways model (Diez Roux, 2012). Diez Roux (2012) purported that both models allow public health researchers to understand the individual, environmental, and community context of health and health behavior. In this study, I used both theories to provide a framework for investigating whether socioeconomic characteristics, hospital type, patient demographics, and hospital characteristics are parallel to CDI incidence trends and whether disparities among them exist. These models can influence social change by policy modification to reduce disparities in CDI prevention practices and quality of care among patients of varying demographic backgrounds, within different socioeconomic groups, and in different hospital levels.

Fundamental Cause Model

The fundamental cause model provided a foundation for investigating the implications of socioeconomic conditions as well as sociodemographic variations in disease incidence and healthcare quality of services (Phelan, Link, & Tehranifar, 2010; Diez Roux, 2012). Diez Roux (2012) and Phelan and Link (2015) used the fundamental cause model to identify disparities in health and disease incidence through understanding the cultural ideals, social norms, racism, discrimination, and the overall social gradient of communities relative to health behavior, opportunities, and barriers. The model was also used to investigate whether such disparities were attributable to the differences in quality care across different socioeconomic groups.

In this study, I used the fundamental cause theory to explore the research question regarding the relationship between patient demographic data and CDI incidence in New Mexico acute care hospitals. It served as a guide to help me observe if there were similar patient socioeconomic patterns among acute care hospitals with reported high CDI cases and whether these patterns presented a disparity in health practices and CDI prevention. For this study, the variables of interest included patient age, gender, insurance payment type, income, race, and length of stay. A similar approach to the use of this model to investigate the relationship between hospital health behaviors and patient socioeconomic characteristics was evident in a study by Quasim (2016). Quasim (2016) used fundamental cause theory to explore the disparities in surgical outcomes among different socioeconomic groups. Quasim (2016) purported that this model can explain the socioeconomic influence on quality, cost, and availability of resources for best health practices. Variables observed included patient length of stay, insurance type, age, gender, income, and race—all of which are characteristics associated with patient socioeconomic and health status (Quasim, 2016).

Pathways Model

Another model, the pathways model, also served as a framework for studying the relationship between distal causes of health and the existence of health disparities (Diez Roux, 2012). Zieger, Redding, Leath, and Carter (2014) used the pathways model to develop the Pathways Community HUB, which promoted the standardization of healthcare practices across multiple community hospitals and limited inadequacies of health services based on patient socioeconomic level and barriers. Specifically, Zieger et al. (2014) used the model to target the barriers of care to at-risk patients and develop interventions to provide better access and services of community health to these patient populations. The barriers Zieger et al. (2014) identified can serve as origins to inequities in quality of care.

In contrast to the fundamental cause model, the pathways model traces the lineage of social and environmental factors that result in the present health behavior or health disparity independent of cultural norms or discrimination. For example, changes to a hospital policy or limited hygiene resources for that hospital may be a contributing factor to the sudden change in quality of health for a target community. In this study, the pathways model was implemented to investigate whether acute care hospital type and types of services served as precursors to CDI risk level. These variables are points of origins and can encourage ancillary research to identify if differences in admission policies, practices, populations, and protocols among teaching and nonteaching hospitals in different counties present a significant relationship to hospital quality of care, prevention practices, and healthcare equity.

Nature of Study

The study approach I used for the research questions was a nonexperimental cross-sectional study design using secondary data. Because I investigated the association between CDI diagnoses and specific hospital and patient variables for 2014 and 2015, the cross-sectional design was implemented with a focus on retrospective analysis.

Specifically, my cross-sectional design focused on exploring the association between CDI diagnoses and multiple variable groups, such as the number of different income groups and insurance types in New Mexico. Other variables that were investigated for association with CDI incidence were patients' demographic information and characteristics (age, gender, ethnicity, number of diagnoses, and length of stay) and the hospital service lines (surgical, medical, injury, etc.) as they aligned with the problem statement.

Secondary data for the analysis for the research question were derived from the Healthcare Cost and Utilization Project (HCUP) data set, specifically the 2014 and 2015 New Mexico Statewide Inpatient data set. Using this data set as the primary source for data collection and review eliminated the incidence of duplicate variables or presence of artifacts during the analysis phase. As actual hospital names and locations were not disclosed in this study for the purpose of identity protection, hospital service lines are categorized as *medical*, *injury*, or *surgical*. Data on the number of CDI cases reported for 2014 and 2015 were derived from the same HCUP data set. The data set also contained the following variables associated with the research hypothesis: patient demographic information, such as age, race, and gender; insurance payer type; length of stay; income group; and number of diagnoses.

Definitions

Key Terms

Standard infection rate (SIR): A measurement used to monitor the risk level of an HAI in a hospital (CDC, 2018). SIR is risk-adjusted to account for differences in hospital size, services, and other differentiating characteristics by creating a baseline that hospitals can measure against (CDC, 2018). This measurement tool was created by the CDC and used by the NHSN (CDC, 2018).

Hospital-acquired infection (HAI): Infections acquired by a patient in a hospital setting (Office of Disease Prevention and Health Promotion, 2018). It can originate from direct contact with a contaminated surface, hospital staff carrying the contagion on their hands or body, or from medical procedures or equipment (Office of Disease Prevention and Health Promotion, 2018). HAIs contribute to a hospital's morbidity and mortality rate; however, the number of cases could be lessened with proper prevention protocols (Office of Disease Prevention and Health Promotion, 2018).

Antimicrobial stewardship: The ability of individuals—particularly healthcare professionals—to properly use antimicrobial agents (Dyar et al., 2017). Examples include hand hygiene compliance and maintaining sanitized surfaces to protect patients and other healthcare staff against harmful microbes and pathogens.

Health disparities: Inequities in health services or status due to differences in population, economic factors, and cultural factors (CDC, 2015a). In this study, the term will pertain to both geographic and socioeconomic differences in health status and services.

Socioeconomic status: The relationship between an individual's social and economic standing and health status (Baker, 2014). Higher social and economic standing have a strong correlation with a more positive health status (Baker, 2014).

Independent Variables

Age: Plays a large part in assessing an individual’s health status and disease risk. For this study, age was grouped in increments of ten years.

Acute care facility: A specific type of hospital facility that provides a wide range of specialty services, such as trauma care, emergency care, and urgent care (Hirshon et al., 2013). The main purpose of an acute care facility is to provide diagnostic, treatment, preventive, and curative services with regards to time sensitivity and individuality of cases (Hirshon et al., 2013).

Gender: Patient identification of male or female sex.

Hospital services: The specialties and types of medical and health services provided by a hospital facility. Examples of services include trauma, cardiac, and intensive care unit. The types of services a hospital provides determines the overall hospital charges.

Length of Stay: A representation of the number of days a patient spends in a hospital from date of admission to date of discharge. It can also be represented as an average at the hospital level.

Median household income quartile: This variable served as a representation of income levels for this study. It is categorized into four quartiles that range from lowest income groups to highest income group.

Number of diagnoses: This is the number of additional medical conditions diagnosed beyond the primary condition. This is also termed *comorbidities* in most literature. For this study, the number of diagnoses were categorized into six groups using the Minnesota Tiering system from lowest number of diagnosis (beyond the primary diagnosis) to highest number of diagnoses (Haas et al., 2013).

Payer (insurance) type: What a patient uses to pay for medical services and costs. Insurance type can be influences by factors such as type of practice, location of facility, quality of services, and costs of services (Arora et al., 2013).

Race: What the patient physically identifies as. For this study, it is divided into six groups: White, Black, Hispanic (Non-White), Native American, Asian, and other.

Dependent Variables

Clostridium difficile infection (CDI): A bacterial infection of the colon that is contagious and can be transmitted from a contaminated surface to an individual (CDC, 2015). CDI is also closely associated with high antibiotic use (CDC, 2015). Because of these factors and the majority of cases occurring in healthcare environments, it is typically considered an HAI (CDC, 2015).

Assumptions

In this study I observed and reviewed data presented in the HAI progress report for New Mexico acute care hospitals, reported under the NHSN. Only CDI data reported by participating New Mexico care hospitals were included. The data presented in this study were assumed to be current and a factual representation of the healthcare facilities' CDI reports, population characteristics, and NHSN reporting protocols. The information collected from HCUP and the New Mexico's Indicator Based Information System (NM-IBIS) was also assumed to be current, factual, and objective as the data were derived from the databases of participating hospitals and have undergone review by quality and records specialists.

Scope and Delimitations

The scope of this study was limited to acute care and community hospitals in New Mexico counties. This excluded long-term care facilities, rehabilitation centers, federal hospitals, and skilled nursing facilities. Although these facilities have reported cases and incidences of CDI in New Mexico, they were not included in the NHSN reports due to differences in reporting protocols and NHSN reporting criteria. With the same justification, reported community-acquired CDI cases were excluded from this study.

The NHSN presents reports on several other common HAIs, including central line-associated bloodstream infections, catheter-associated urinary tract infections, surgical site infections, vancomycin-resistant enterococci, and methicillin-resistant staphylococcus aureus. However, they were not explored in this study as the New Mexico NHSN reports for each of these HAIs did not warrant the same public health surveillance needs as CDI; based on SIRs, CDI was the only HAI in New Mexico that scored below the national baseline for three consecutive years. The outcome of the study findings is specific to the New Mexico population.

Literature Search Strategy

In this study, I used several literature search tools to locate and review literature appropriate for the context of this research. EBSCO, PubMed, Science Direct, ProQuest, and Medline were common search databases used for obtaining the literature presented in this study. Walden University's library services, Walden University's dissertation database, and Google Scholar were also used. Search terms included *clostridium difficile*, *length of Stay*, *geographic location*, *regional variation*, *disparities*, *race*, *age*, and *aging population* in one or more types of combinations. Selected literature for review were categorized into the following to look for similarities and repeated key information: *hospital type*, *hospital characteristics*, *patient demographics*, *racial* and *socioeconomic disparities*. Only literature that met the criteria of being published from 2013 to 2018 were included. Literature that met the search criteria but did not meet the timeline requirement were excluded.

Inclusion Criteria

Studies that were valid and peer-reviewed were included in the search strategy. The literature was also reviewed to ensure it originated from a reliable source, such as an academic journal or official government website. Government websites included the CDC, World Health Organization, Office of Disease Prevention and Health Promotion, and state public health websites. Although the literature searched focused on studies conducted in the United States, some studies performed outside the United States were included due to the limited information available for certain variables and search terms and topics in the United States. Such literature was used as supporting evidence, due to similarities in contexts and concepts, rather than explanatory means for the variables presented in this study. A majority of the literature reviewed was based on a retrospective analysis.

Exclusion Criteria

Literature that deviated from the main ideas of this study, after being reviewed, was excluded. Literature that was in a different language, did not meet the timeline criteria, or did not originate from a valid academic or government source was also excluded. Studies that were biased or were not empirically sound were not reviewed.

Literature Review

Socioeconomic Characteristics

Insurance type and income can be influenced by one another (Kaestner & Lubotsky, 2016). For example, income can change based on employment, age, marriage, and location status. Insurance type can also be influenced by similar characteristics and income. To account for the differences in socioeconomic classification, age, gender, and race, and number of diagnoses were grouped separately from insurance type and income for this study. This was to model an approach similar to Farell et al.’s (2015), which was differentiating patient demographic and social characteristics and impact on health.

Income and CDI risk. Several research publications have identified a correlation between income level and CDI risk. The literature coins income differences in CDI as an observation for socioeconomic disparity. Although literature exists for both community-acquired and hospital-acquired CDIand the impact of socioeconomic factors on level of risk, I specifically reviewed the literature for hospital-acquired CDI. Miller et. al. (2016), Olanipekun et al. (2016), and Becerra et al. (2015) examined the role of income in CDI incidence. These studies used income quartiles based on the median income of a ZIP code region (Becerra et al., 2015; Miller et al., 2016; Olanipekun et al., 2016). Becerra et al. (2015) determined that higher income was associated with an increased risk for CDI. The assessment of income association with CDI risk was conducted using a logistic regression analysis. Miller et al. (2016) and Olanipekun et al. (2016), however, did not isolate income as a predictor of CDI incidence risk. Rather, they included income quartile as a patient-level characteristic and its predictability in length of stay in those with and without CDI (Miller et al., 2016; Olanipekun et al., 2016). Both studies determined that patient-level characteristics, such as income, had little impact on length of stay, despite the association between length of stay and CDI (Miller et al., 2016; Olanipekun et al., 2016).

A subtle difference identified in Becerra et al. (2015), Olanipekun et al., (2016), and Miller et al. (2016) in contrast to the focus of this study is that income quartile is considered a patient-level characteristic. However, Berkowitz, Traore, Singer, and Atlas (2015) classified income as a socioeconomic indicator as it can change overtime, such as address, marital status, and education. Race and gender, on the other hand, were static characteristics unique to a patient (Berkowitz et al. 2015). Farell et al. (2015) differentiated education and ethnicity, for example, as social and demographic traits. Lee et al. (2018) also classified income as a socioeconomic factor, yet the same author indicated age, race, and gender as socioeconomic characteristics.

Insurance type and CDI risk. Insurance type has been classified as a demographic or socioeconomic characteristic of a patient profile in previous research. Kassam et al. (2016) incorporated insurance type as a demographic characteristic among other characteristics, such as income, gender, and race. In their study, Medicare users accounted for a majority of CDI-related hospitalizations (Kassam et al., 2016). Reveles, Lee, Boyd, and Frei (2014) included insurance as a patient characteristic and found that more Medicare insurance users had a significant association with CDI incidence. Both studies attributed to the idea that many of the patients in the study are Medicare users, with Medicaid following as the second most used insurance (Reveles et al., 2014; Kassam et al., 2016).

An important matter to note about insurance payer type and its association with healthcare services is the impact it has on quality and type of care. In a study published in the *American Journal of Ethics*, it was posited that what a patient pays for healthcare services is related to the healthcare setting, location, and ZIP code (Arora, Moriates, & Shah, 2015). Spencer, Gaskin, and Roberts (2013) examined the impact of insurance payer types on quality of care within a hospital. Reimbursement rates, physician characteristics, cost of services, and quality improvement efforts all are impacted by different insurance groups (Arora et al., 2013). Weissman, Vogeli, and Levy (2013) discussed the views of both studies in their own research. They found that geographic location of a hospital and quality of care were determinants of the payer type commonly used in a healthcare facility (Weissman et al., 2013). Although Medicare accounted for a large number of patients in the population, the quality of care in health services was identified by private insurance payers (Weissman et al., 2013). The findings of these studies served as a basis for the investigation of whether the number of CDI cases in a hospital is due to services that insurance groups pay for treatment and prevention efforts of CDI and characteristics of the hospital.

Hospital Service Lines

Emergency departments and CDI incidence. Emergency departments (EDs) treat a wide variety of urgent medical conditions and are highly complex in their operations and environments (Liang, Theodoro, Schuur, & Marschall, 2014). Because of this, the risk of transmitting and acquiring a pathogen is prevalent, and prevention efforts can be easily bypassed (Liang et al., 2014). With this knowledge, several studies sought to identify whether CDI risk is probable in high-volume environments such as the EDs.

Current studies have investigated the burden of CDI in EDs. Smith, Wuerth, Wiemken, and Arnold (2015) found that reported cases of CDI in EDs were patients who were female, over the age of 85, and from the Northeast region of the United States. Pant et al. (2017) found a similar insight within the same timeframe. In both studies the researchers used the Nationwide Emergency Department Sample to review the incidence of CDI in EDs (Smith et al., 2015; Pant et al., 2017). However, the findings of the characteristics of patients' ED visits and CDI diagnoses were reported differently. The percentage of CDI-related ED visits for adults younger than 65 increased more exponentially than those for adults over the age of 65 (Pant et al., 2017).

In both studies, researchers argued that although ED visits were strongly linked with community-onset CDI, little is known about the development of CDI in an ED, irrespective of community-based acquisition (Pulia et al., 2015; Smith et al., 2015; Pant et al., 2017). The authors of both studies, as well as others, identified the importance of investigating this population group because they sought to determine the level of standard precaution practiced in EDs (Pulia et al., 2015; Smith et al. 2015; Pant et al., 2017). They also questioned whether antimicrobial stewardship is used for patients admitted to an ED with primary or secondary diagnosis of CDI (Pulia et al., 2015; Smith et al., 2015).

Trauma centers and CDI incidence. Morteanu, Chirt, and Buran (2015) and Vanzant et al. (2015) discovered an increase in CDI among trauma patients. The major characteristics that both studies found in trauma patients with CDI were that they have longer lengths of stay and face immunosuppression due to traumatic injury (Morteanu et al., 2015; Vanzant et al., 2015). Immunosuppression often calls for the use of antibiotics and is associated with hospitalizations for recovery, yet this also raises the risk of CDI acquisition.

Neither study included discussions of whether CDI is present in trauma injuries rather than acquired after a traumatic injury. Further investigation can be implemented to determine if such a correlation exists as little research exists on CDI acquisition in hospital trauma centers. Existing literature does cover, however, trauma intensive care units and incidence of CDI. The concern with this finding is the use of *trauma centers* and *intensive care units*. Some studies used the two terms interchangeably whereas others referred to the two departments as different hospital services. This also prompts for further research to be conducted specifically on trauma patients and CDI incidence with the exclusion of intensive care unit admission.

Intensive care units and CDI incidence. There is extensive research literature on the presence of CDI in the intensive care unit (ICU) setting. Pretcher, Katzer, Bauer, and Stallman (2017), Karanika et al. (2015), and Zilberg and Shorr (2013) mention that patients admitted into an ICU are at greater risk for CDI. All three studies have attributed

CDI incidence in ICUs to increased length of stay, older age, and utilization of hospital resources (costs, equipment, etc.) (Pretcher et al., 2017; Karanika et al., 2015; & Zilberg & Shorr, 2013). Yet, it is not mentioned whether length of stay in the ICU increases CDI risk. Standard precaution and investigation of environmental disinfection and hand hygiene practices were risk factors conferred to contribute to CDI prevalence in ICUs in studies by Zilberg and Shorr (2013) and You, Song, Cho, and Lee (2014).

Interestingly, the use of proton pump inhibitors has been mentioned in multiple studies as a risk factor for CDI prevalence in intensive care units (Barletta & Sclar, 2014; Buendgens et al., 2014; Lewis et al., 2016). Proton pump inhibitors are prescription medications associated with gastrointestinal disorders (Fusaro, Giannini, & Galieni, 2016). There is a gap in the literature regarding gastrointestinal conditions and CDI prevalence. In the scope of public health, further research would need to be investigated on the use and distribution of proton pump inhibitors and gastrointestinal disorders in different health populations. Although studies pertaining to the correlation of CDI and the use of proton pump inhibitors exist, further research in the investigation on the association between gastrointestinal disorders, ICU admission, and CDI may assist in providing more insight in the relationship between proton pump inhibitor usage and CDI prevalence.

Conversely, Bouza et al. (2015) contend that the prevalence of CDI in ICUs has decreased of the years. The findings in their study showed a decrease in CDI incidence in intensive care units but an increase in other units over a ten-year period in a participating large teaching hospital (Bouza et al., 2015). The authors posit that the decrease in CDI incidence is attributable to improved infection control measures and early diagnosis of CDI (Bouza et al., 2015). The suggestion of early diagnosis as an intervention was not mentioned in the other studies mentioned in this section.

Surgical centers and CDI incidence. Studies such as that conducted by Guh et al. (2017) and Li, Wilson, Nylander, Smith, Lynn, and Gunnar (2016) postulate that CDI risk is highest in emergency departments and surgical centers due to the high frequency of interaction between care providers and patients. Some of the characteristics that support this notion, especially for surgical centers, is that patients that are admitted for surgical procedures have the risk of encountering a surgical site infection which would involve the use of antibiotics (Li et al., 2016). As common knowledge in the study of CDI prevalence, prolonged antibiotic use increases the risk of CDI in these patients (Guh et al., 2017). The type and complexity of surgical procedures has a linear relationship with the level of risk of CDI in patients (Li et al., 2016).

Another common trait with CDI incidence in surgery patients is longer hospital stays (Guh et al., 2017; Flagg et al., 2014) and associated comorbidities (Guh et al., 2017; Li et al., 2016; & Flagg et. al., 2014). Mortality risk is increased in surgical patients, especially cardiac surgery, with CDI (Li et al., 2016; Flagg et al., 2014; & Keshavamurthy et al., 2014). Cardiac surgery, according to Flagg et al. (2014), was also associated with high burden of comorbid conditions.

Hospital Teaching Status

Hospital teaching status and CDI incidence. The academic status of a healthcare facility can provide clues on the quality of care and performance of such facilities. Academic healthcare facilities differ from non-academic facilities in the services they provide, the quality of care, their location (urban versus rural) and the costs (Shahian, Liu, Meyer, & Normand, 2014). Although both are regarded as acute care facilities, teaching hospitals are more reputable as they provide opportunities for training, research, and presenting new ideas and health innovations to the medical field (Shahian, Liu, Meyer, & Normand, 2014). Therefore, they provide a different and more progressive standard approach to the delivery of healthcare to the public (Burke et al., 2017; Bekelis et al., 2018) compared to non-academic facilities. On the other hand, academic acute care facilities are just as susceptible to cases of nosocomial infections as their non-teaching counterparts.

Several different research studies have discussed the presence of nosocomial infections in teaching hospitals. A study conducted by Smetana, Čečetková, and Chlíbek (2014) found a 4.3% prevalence rate of nosocomial infections such as Staphylococcus aureus and Escherichia Coli in 12 university hospitals in Czech Republic. Another study performed by Press et al. (2013) found that teaching hospitals had higher readmission rates compared to non-teaching hospitals between 2009 and 2011. Press et al. (2013) mentions that readmission rates are used as a measure for hospital quality ranking, patient satisfaction, and hospital performance. These measures can be associated with presence of HAIs in a hospital.

Other Factors Associated with CDI Risk

Comorbid conditions and correlation with CDI risks. Comorbidities are one of the most common risk factors associated with CDI (Miller, Polgreen, Covanaugh, &

Polgreen, 2016). Because the presence of comorbidities differs for a variety of CDI research studies, researchers often adjust analyses to account for the possibility of comorbidities presenting as confounders (Wilcoz, Chalmers, Nord, Freeman, & Bouza, 2016). Other studies observe the presence of comorbidities and their association with CDI (Miller et al., 2016); Tiscinesi et al., 2015). The number and types of comorbidities, especially when including age, determines the severity index and level of risk of CDI (Wilcox et al., 2017). The Elixhauser comorbidity index is a commonly used measure to identify the number of comorbid conditions and the correlation with CDI (Harris et al., 2018; Miller et al., 2016; & Warner et al., 2013). Yet, the Charlson comorbidity index has been present in more studies as a tool for comorbidity indexing in CDI risk (Archbald-Pannone, McMurry, Guerrant, & Warren, 2-15; Magee et al., 2015, Rodriguez-Pardo et al., 2013).

There are a number of studies that identify specific comorbidities associated with CDI risks. Investigating the presence of specific comorbidities allows for researchers to learn more about hospital characteristics, such as service-lines available to treat certain conditions, and population risk factors. For this study, several research literatures were reviewed to identify common comorbidities present in CDI diagnosis. Some of the most common comorbidities presented were: hypertension (Reveles et al., 2017), diabetes (Reveles et al., 2017; & Stevens, Concannon, Van Wijngaarden, & MGregor, 2013), respiratory conditions (Reveles et al., 2017; Stevens et al., 2013; & Tschudin et al., 2013), antibiotic use (Reveles et al., 2017; Stevens et al., 2013; & Tschudin et al., 2013), cancer (Reveles et al., 2017; Stevens et al., 2013; & Tschudin et al., 2013), and irritable bowel syndrome and other gastrointestinal disorders (Reveles et al., 2017;Vidigni & Surawicz, 2015; & Tschudin et al., 2013).

Healthcare staff CDI knowledge and education. Just as antimicrobial stewardship, standard precaution, and strict protocols are necessary for CDI prevention, hospital staff knowledge and education are important to execute these practices for CDI prevention. The fact that non-compliance and low-performing clinical practice is ever-present globally in healthcare settings in regard to CDI prevention has prompted researchers to investigate the knowledge level, behaviors, and attitudes of healthcare staff (Burnett, Kearney, Johnston, Corlett, & MacGillivray, 2013). Burnett and colleagues (2013) have investigated eleven research studies to gather information on healthcare staff knowledge and perception of CDI and methicillin-resistant staphylococcus aureus risk. The authors reviewed these studies to conceptualize an overall picture of the attitudes and behaviors of healthcare professionals towards infectious disease prevention and standard precaution and whether it plays a significant role in hospital care quality (Burnett et al., 2013). Before selecting the eleven research literatures of interest, the authors conducted extensive literature reviews, screening, inclusion, and exclusion process. From the screening, 3,448 articles were identified. Further screening resulted in eleven qualified articles (Burnett et al., 2013).

Recurring trends that were identified in the reviewed literature included the utilization of survey methods for the quantitative studies and interview methods for the qualitative studies (Burnett et al., 2013). A mixed approach was identified in one study (Burnett et al., 2013). Physicians and nurses were the primary participants identified in the study, while additional participants included volunteers, allied healthcare workers, therapists, and infection control professionals (Burnett et al., 2013). According to Burnett et al. (2013), only four studies focused on CDI. In these studies, healthcare staff overall indicated that common issues influencing their CDI perception included lack in competency, unclear policies, poor education, and lack of confidence (Burnett et al., 2013). There were also self-reports of poor infection prevention practices among clinical care staff and infection control personnel (Burnett et al., 2013).

A similar quantitative study was conducted in the University of New Mexico Health Science Center which serves as a major teaching hospital. (Fayerberg, Brouchard, & Kelliem 2013). The study focused on the CDI standard precaution practices and infection prevention behaviors and attitudes of postgraduate residents. The results of the questionnaires determined that many participants presented a gap in knowledge of the following: CDI tests used by hospital, standard precaution procedures, antimicrobial stewardship, appropriate hand hygiene, and therapy interventions (Fayerberg et al., 2013). Fayerberg et al. (2013) also identified similar findings in a US survey completed by 90 medical residents which suggest that this may have been a national issue.

In a study by Roth, Parker, Wale, and Warrier (2014), a survey-based study was conducted to analyze doctors' and nurses' knowledge base of different CDI-related scenarios. Some of the doctors and nurses had gone to a CDI-related educational seminar prior to completing the survey; approximated three-fourths of the participants of the survey did not attend the seminar (Roth et al., 2014). Although both groups did not answer all the survey questions correctly, the group that attended the educational seminal performed better on the survey than the other group (Roth et al., 2014). The findings imply that there is a knowledge gap in CDI prevention among healthcare staff and that education on the subject matter is a suggested intervention (Roth et al., 2014).

Differences in resource availability for CDI prevention between urban and rural communities. The standardization of infection control intervention and practices has been observed by various researchers. Stevenson et al. (2014) assessed the effectiveness of the implementation of an infection control program for rural hospitals in Idaho and Utah, the study aimed to determine if the implementation of such programs in a region with limited resources is viable. A study with a similar inquiry and approach is observed in Haun et al. (2014). The authors examined the clostridium difficile prevention practices of rural hospitals in Wisconsin. Both Haun et al (2014) and Stevenson et al. (2014) used surveys as a qualitative approach to identify the availability of resources, as well as the barriers and knowledge of staff in rural hospitals. Both studies have found that prevention practices between urban and rural hospitals differed significantly and lack of resources was one of the primary factors that differentiated the effectiveness of surveillance practices between the two population types (Haun et al., 2014, Stevenson et al., 2014).

On the other hand, Haun et al. (2014) mention that rural hospitals have fewer resources for CDI and other HAI prevention programs compared to the urban counties because it is perceived that there are fewer cases and less risk for contracting HAI due to smaller population size. Other possible causes include fewer mandates for reporting due to smaller patient counts, differences in antibiotic prescribing practices, limited infection control specialist availability, and limited means for standardization of lab facilities and materials for diagnosing CDI (Haun et al., 2014). Stesland, Akamimigbo, Glass, Zabinski (2013) note that Medicare beneficiaries in rural hospitals had comparable quality of services to urban facilities. After researchers have compared the amount and quality of services rural facilities received to urban facilities, they found that there were some similarities to the two, despite the fact that rural facilities received more than urban facilities in special Medicare payments (Stesland, 2013).

Patient Characteristics and CDI Risk

Gender correlation with CDI risk. Gender and age are variables that are often analyzed to determine level of risk for CDI (Goudarzi, Seyedjavadi, Goudarzi, Aghddam, & Nazeri, 2014) and recurrent CDI (Mani, Rybicki, Jagadeesk, & Mossad, 2016). Yet, there are a limited number of studies that investigate the significance of gender differences in CDI prevalence in the United States. According to Natarajan et al. (2015), most research literature that explore CDI rates and gender focused on the male population. Few studies, such as that by Chitnis et al. (2013) and Lessa et al. (2014), found that females had a higher risk for CDI incidence than males. From investigation of other research literature, studies on CDI that is associated with gender involves other variables of focus such as comorbidities; which would be understood if gender were a significant factor associated with CDI as some comorbid conditions are gender-related (Natarajan et al., 2015).

Natarajan et al. (2015) focus on the correlation of CDI risks and gender. The study involved the investigation of two different CDI strains: non-toxigenic CDI (NTCD) and toxigenic CDI (Natarajan et al., 2015). Patient demographic information, including gender, was obtained from an electronic health system (Natarajan et al., 2015). The participants were followed for one year and reevaluated again for comparison to the baseline data (Natarajan et al., 2015). Based on the analyses and results of the study, Natarajan and colleagues (2015) discovered that women with NTCD were more likely to develop short-term risk of CDI than males. On the other hand, long-term risk of CDI in those with NTCD were similar for both genders (Natarajan et al., 2015). According to Natarajan et al. (2015), women exhibited a higher rate of CDI than men. The authors posit that differences in gut microbe and hormonal influence may be contributing factors (Natarajan et al., 2015). It is suggested that further research be conducted on the correlation of CDI and gender as not enough evidence is available to claim the significance and association.

Race and racial disparity in CDI prevalence. There exist many publications that explore the presence of racial disparities in CDI prevalence. Interestingly, whites exhibited the greatest incidence risk for CDI compared to other races (Argamany, Delgado, & Reveles, 2016; Mao, Kelly, & Machan, 2015, Lessa et al., 2014). A common disparity that was found among CDI prevalence among different races was access issues. Non-whites had limited access to health services such as antibiotic therapy and shorter length of stay (Mao et al., 2015) which may influence level of CDI risk; CDI risk is closely associated with length of stay (Daneman et al., 2017; Miller et al., 2016) and antibiotic use (Daneman et al., 2017). However, the study by Argamany et al. (2016) is contradicting in the idea that non-whites had a shorter length of stay as they found that blacks had a longer length of stay but still a lower CDI prevalence rate than whites.

Although a study by Reveles et al. (2017) presented similar findings, it was excluded from this review because the population of interest was based in the Veterans Health Administration system, which has predominant patient characteristics with regards to age, race, and gender.

Economic characteristics were not major factors explored in CDI incidence and racial disparity correlations, as mentioned in studies by Bakullari et al. (2014) and Argamany et al. (2016). For instance, Asians have a higher income, according to (Mao et al., 2015), but lower rates of CDI prevalence. However, Bakullari et al. (2014) had a conflicting finding where Asians had a higher risk for CDI than whites. Similar to gender and age, some comorbid conditions may be associated with race, which could likely influence CDI prevalence. Conflicting findings prompt for further, more standardized research of CDI in other populations, especially underrepresented ethnic groups (Yang, Rider, Baer, Ducoffe, & Hu, 2016; Bakullari et al., 2014).

Social Change Implications

There were several social change implications that this study attempted to address based on the multiple research hypotheses. The first area of interest was the need to determine how health services and resources are disseminated across different socioeconomic groups and different hospital specialties. According to Li et al. (2013), economic and social disparities were likely to impact health outcomes and availability of resources. This study will assist in developing or standardizing healthcare practices and availability of resources across the nation. The other social change implication regards the relationship between hospital service line and the estimated level of cost of services per number of service lines. The types of health services offered affect Medicare reimbursement amount. The more services, the greater financial gain of the hospital; this prompted investigation of what financial influence a hospital may have in CDI prevention programs (Dudeck, 2013). This study may help prompt policymakers and hospitals in making more healthcare services available to patients of different financial make; especially developing programs or services for income-restricted patients.

There was a knowledge gap in the research literature that explores the relationship between socioeconomic characteristics, hospital service line, and relationship to CDI. This was especially important for the state of New Mexico as limited research investigated all participating facilities. The available research literature centered on New Mexico CDI rates only explored cases in Bernalillo County. Chapter 2 provides details on the research design plan and methodology used to explore the relationship between CDI rates and hospital and patient characteristics of New Mexico residents.

Section 2: Research Design and Data Collection

Purpose of Study

The purpose of this study was to explore the relationship between CDI incidences in New Mexico acute care facilities and acute care hospital characteristics (service-lines), socioeconomic characteristics, and patient population demographics. The previous chapter provided an overview of the public health implications of this subject matter and its application to social change. This study examined the research problem and the research hypothesis through secondary analysis using a quantitative approach. This chapter discusses the methodology used to analyze the variables of interest. Specific components of the methodology plan include the research design, population characteristics, data source, data analysis tools and construction, and threats to validity. The ethical considerations and concerns of the methodology plan are summarized in the last section of the chapter.

Research Design

Variables of Interest

The independent variables of this study included: New Mexico acute care facilities, socioeconomic characteristics (insurance type and income group), hospital characteristics (service-line), and patient demographic information and characteristics. The dependent variables included reported CDI cases across facilities. This study utilized a quantitative approach to analyze the variables of interest. These variables were grouped based on similar characteristics rather than randomized for comparison of trends, patterns, and traits and analysis of level of significance.

The cross-sectional design method was used to examine the relationship between the variables. Because this study observed the characteristics of the variables based on grouping, is not under a time constraint, and is not dependent on change of primary variable, the cross-sectional design served as an appropriate research analysis plan to address the research questions. The cross-sectional design for the observation of CDI incidence and associated variables included snapshots of outcomes in different years (2014 and 2015) and those years were combined to determine the significance of the CDI outcomes overall. In addition, the cross-sectional approach to research design was appropriate for use in organizing and analyzing data that already exist. In the instance of this research study, the data collection approach was the review of secondary data from the HCUP database. This is discussed in more detail in a later section.

Data Collection Source and Procedure

Healthcare Cost and Utilization Project (HCUP). Secondary data collection was the method used to obtain the required variables for this study. The CDI, patient characteristics, hospital characteristics, and New Mexico population urban and rural sizes were obtained from the Healthcare Cost and Utilization Project (HCUP) database. HCUP is a nationwide (U.S.) database governed by the Agency of Health Research and Quality (AHRQ) department under the United States Department of Health and Human Services (USDHHS). The database consists of multiple annual health reports collected from different participating states across the nation. However, not all health reports are consistent across each state due to different reporting protocols, resources, and state population demographics. The main objective of HCUP's data acquisition from outside partners and stakeholders was to explore research inquiries of varying nature pertaining to cost and utilization of health services, access trends, patient care and health trends, and treatment patterns at the state and national level (Murphy, Alavi, & Maykel, 2013). Data was collected through partnerships with health and research organizations found at the local, state, federal, private, and regional levels (Murphy et al., 2013).

The data collected by HCUP through AHRQ is administrative and then converted to a database format that is standardized across all categories. The databases in HCUP are divided into several distinct categories including the following: National Inpatient Sample; Kids Inpatient Database; Nationwide Readmission Database; State Inpatient Database; State Ambulatory Surgery and Services Database; and the State Emergency Department Database. For the purposes of this study and the focus on one state inpatient data, the State Inpatient Database will be utilized for statistical analysis of the research questions.

Obtaining the data set. The process for obtaining the required variables from the database included mandatory online training for HIPPA laws and HCUP privacy policies, acknowledgement of the data use agreement, statement of research purpose, and electronic submission of application packet. The availability of variables for the indicated years for the state of New Mexico were reviewed and undergone a thorough selection process to finalize the variables that were appropriate to the study approach and for appropriation of data analysis. Requested data sets were made available by state and year. The request was reviewed by the Agency for Healthcare Research and Quality. Approved data was mailed out to the designated recipient for private use. The data was obtained in an electronic format and accessed via a secured HCUP DVD in a secured environment.

Study Population and Participants

New Mexico Population Characteristics

Collection of population data. Population demographic information was collected by the Economic Research and Analysis Bureau of the New Mexico Department of Workforce Solutions (NMDWS) (New Mexico Department of Workforce Solutions [NMDWS], 2015; NMDWS, 2016). The Economic Research and Analysis Bureau makes the annual report and data available to the public for informational, research, and academic use including other objectives (NMDWS, 2015; NMDWS; 2016). The Bureau also partners with the Bureau of Labor statistics (BLS) of the United States Department of Labor and Statistics (NMDWS, 2015; NMDWS; 2016). Many of the organizations and programs that participated in the annual reporting of the socioeconomic indicators for the state of New Mexico, such as the Current Employment Statistics Program (CES) and the Current Population Survey (CPS), utilized survey methods to obtain employment data from multiple businesses (NMDWS, 2015; NMDWS; 2016). The data collected was an estimate of the population averages and characteristics; it may not be representative of all individuals residing in New Mexico.

Total population statistics. New Mexico is one of the established 50 states in the United States of America and is the 36th most populous state in the country (NMDWS, 2015; NMDWS; 2016). The state’s total population for 2014 was 2,085,572 with two-thirds of this population residing in metropolitan counties (NMDWS, 2015). In 2015, the reported total population was 2,085,572; 2015 metropolitan total estimates were not provided in this report (NMDWS, 2016). The most populous metropolitan county in New Mexico for both 2014 and 2015 is Bernalillo County (675,551 and 676,685 respectively) and the least populous non-metropolitan county is Harding (683 and 698 respectively) (NMDWS, 2015; NMDWS; 2016). According to the findings in the 2015 report (NMDWS, 2016), researchers purported that the change in population characteristics and statistics was attributed to births rates within the state. The total population increase attributable to birth rate was 53,203 which surpassed the total population migration of 27,115 (NMDWS, 2016). Curry County had the greatest increase in population by birth rate (1.1 percent) while Harding had the highest rate of migration (0.5 percent) (NMDWS, 2016).

Population age and gender statistics. For New Mexico's 2014 data (NMDWS, 2015), the average age of residents was 37.1 years. The average age for the 2015 report was 37.3 years (NMDWS, 2017). The oldest and youngest median age for 2014 are 59.0 years in Catron country and 29.4 years in Roosevelt County (NMDWS, 2015). The statistics for 2015 were similar regarding oldest and youngest median age; Catron County had the highest median age of 60.1 and Roosevelt had the lowest median age of 30.2 years (NMDWS, 2016). In 2014, men displayed both the oldest and youngest median ages (59.7 and 28.6 respectively) (NMDWS, 2015). Women had the oldest age median at 58.3 years and the youngest median age at 30.3(NMDWS, 2015). According to the 2015 report, men displayed bother the oldest and youngest median ages (61.1 and 29.2 respectively) (NMDWS, 2016). In the 2015 report, women had presented with the oldest median age of 59.0 years and youngest median age of 31.3 years (NMDWS, 2017). The greatest concentrated age group for the New Mexico population for both 2014 and 2015 was the range of 20 to 24 years of age (NMDWS, 2015; NMDWS; 2016).

Population race statistics. The most populous race in New Mexico for 2014 was the Hispanic (Latino) group, making up 47.7% of the population (NMDWS, 2015). The second largest racial group were Whites (38.9%) followed by American Indian (8.6%), Blacks/African American (1.9%), Asian (1.4%) and others (>2.0%) (NMDWS, 2015). Mora County had the highest population of Hispanics (80.6%) (NMDWS, 2015). Catron County had the highest percentage of Whites (74.9%) (NMDWS, 2015). Curry County had the percentage of Blacks (5.7) (NMDWS, 2015). The highest population of American Indians reside in McKinley County (72.6%) and the highest population of Asians reside in Los Alamos (6.4%) (NMDWS, 2015). De Baca County had the highest percentage of mixed races within the population (2.0%) (NMDWS, 2015).

For 2015, the Hispanic (Latino) racial group still accounted for the largest racial group in New Mexico (48.0%) (NMDWS, 2016). White remained the next largest racial group (38.4%) followed by American Indian (8.6), Black/African American (1.9%), Asian (1.5%), and other (<2.0%) (NMDWS, 2016). The 2015 race population concentration by county is the same as 2014 with differing percentages for each race: Mora county has the highest population of Hispanics (80.2%), Catron has the highest percentage of Whites (74.7%) as well as the highest population of mixed race (2.3%) (NMDWS, 2016). The highest percentage of Blacks is in the Curry County (5.5%) and

American Indians is McKinley (73.2%) (NMDWS, 2016). Los Alamos had the highest population of Asians (6.6) (NMDWS, 2016).

Population socioeconomic statistics. The 2014 average household income for New Mexico residents was $44,803 (NMDWS, 2015). The Los Alamos county had the highest household income for 2014 while Mora county had the lowest ($105,989 and $24,425 respectively) (NMDWS, 2015). The average per-capita income for 2014 was $37,091 (NMDWS, 2015) and $38,457 for 2015 (NMDWS, 2016). The county of Los Alamos displayed the highest per-capita personal income ($62,619) and McKinley displayed the lowest ($23,789) for 2014 (NMDWS, 2016). The percentage of individuals at the poverty-line in the 2014 report was 20.6% (NMDWS, 2016); 23.0% of females and 25.5% of Hispanics accounted for the groups with the highest poverty rate (NMDWS, 2016).

The average household income for 2015 was $45,382 (NMDWS, 2017). Los Alamos was still ranked as the county with the highest household income ($101,934) while Mora continued to present as the county with the lowest household income ($23,822) (NMDWS, 2017). The 2015 average per-capita income in New Mexico was $37,938 (NMDWS, 2017) with the highest per-capita income found in Los Alamos and the lowest per-capita income found in McKinley ($65,317 and $24,640 respectively) (NMDWS, 2017). The reported percentage of individuals at the poverty-line for 2015 was 19.8% (NMDWS, 2017). Females (21.1%), Hispanics (24.8%), and those under the age of 18 (28.6%) accounted for the groups with the highest poverty rate (NMDWS, 2017). In 2015, 13.1% of the population did not have health insurance (U.S. Census Bureau, 2017).

Target Population

The target population was determined by reviewing the information and data reports provided in NHSN, the American Hospital Association [AHA] Annual Survey Report (AHAASR), and HCUP. The years in which the population was observed and determined for this study were 2014 and 2015. The population of interest were New Mexico residents that have been admitted to a hospital facility within the 2014 and 2015 time-period. The participants were residents in any of the 33 New Mexico counties. All age groups over 18 years, ethnic groups, and genders were taken into consideration.

The American Hospital Association [AHA] Annual Survey Report identified 37 healthcare facilities in New Mexico in 2014 and 36 in 2015 (American Hospital Association [AHA], 2017) with a hospital bed per 1,000 persons ratio of 1.8 for 2014 and 1.9 for 2015 (AHA, 2017). The total population of individuals admitted into a healthcare facility in 2014 is 84 admissions per 1,000 persons and in 2015 is 85 admissions per 1,000 persons (AHA, 2017). The AHA report only accounted for 85% of New Mexico hospitals as federal, long term care, and mental health institutions were not included in the data set. According to the New Mexico Healthcare-associated Infections Annual Report for 2014 and 2015, [34] hospitals participated in the reporting of CDI under the Emerging Infections Program in 2014 (NMHAI, 2015) and [37] in 2015 (NMHAI, 2016). However, since the NHSN only observed acute care facilities, other healthcare facilities such as long-term care facilities (LTCF), Federal Hospitals, and rehabilitation centers were excluded from the report.

Sampling Design

The state of New Mexico is a small state population-wise with a limited number of healthcare facilities. This limited the ability to conduct a random sample of the study participants in order to present a statistically appropriate representation of the population. Therefore, the non-randomization approach was implemented. Due to the intended observation of the CDI cases and hospital characteristics of New Mexico healthcare facilities, a purposive selection of the sampling frame was intended. The purposive sampling of the cases within the sampling frame was appropriate in addressing the research questions which require specific selection of participants and associated variables. However, this sampling technique presented a risk for bias and identification of study participants. Study participants such as patients and hospitals were de-identified and any facility with a cell of reported CDI cases less than ten was excluded, per HCUP guidelines (HCUP, n.d.). Socioeconomic groups will be divided by income quartile and insurance payer type.

Study Participants and Sampling Frame

All administrative data relating to the study participants and sampling frame was obtained from the HCUP New Mexico 2014 and 2015 State Inpatient Data (SID). The total number of participants selected for this study was 327,562. After data-cleaning, the total number of participants studied was 186,669. The population of interest for this study included New Mexico residents age eighteen years and older. Both male and female genders and all races were included in the participant pool. For participants diagnosed with CDI, the diagnosis must have occurred within the 2014 and 2015 period and in a New Mexico acute care or community healthcare facility. All participants must have had admission status in a New Mexico acute or community health facility within the 2014 and 2015 timeframe. Participant marital status and educational level were not characteristics identified in this study. Other variables that have been observed among the study participants included hospital service line, length of stay, number of diagnoses and income group (quartile).

The total number of reported CDI cases for 2014 was 644 (NMHAI, 2015). The total number of reported CDI cases for 2015 was 650 (NMHAI, 2016). New Mexico Healthcare facilities that did not report for both years was excluded from the participant pool. Diagnosis of CDI from a long-term care facility, mental health institution, rehabilitation center and community onset diagnosis were also excluded from the sampling frame. Non-U.S. citizens were not included in the participant pool.

Sample Size

The power analysis statistical tool, G*Power (Faul, Erdfelder, Buchner, & Lang, 2009), was used to calculate the sample sizes appropriate for this research study. Faul et al. (2009) describe G*Power as a statistical analysis program use to calculate the power analysis for multiple statistical tests such as t-tests, Pearson Correlation test, and tests of regression. G*Power is also utilized by researchers in determining the effect size, confidence level, and alpha level appropriate for hypothesis testing (Faul et al., 2009).

For each research hypothesis, a logistic regression statistical test was used. Therefore, a single power analysis calculation was conducted to obtain the appropriate sample size for each research hypothesis. This means that all three research questions shared the same analysis model on G*Power. Because a power analysis was calculated before the research study was conducted, all research questions utilized a-priori analysis to obtain the sample size (Mayr, Erdfelder, Buchner, & Faul, 2007). The calculated alpha was $\alpha=0.05$ while the effect size was calculated as 0.15. At a 95% confidence interval, the accepted sample size was 778.

Instrumentation and Operationalization

Instrumentation of Constructs

NHSN Data Reports through the CDC. Statistical information regarding the reported number of CDI cases in New Mexico healthcare facilities was made available through the NHSN. The NHSN, headed by the CDC, is a national public health surveillance system that tracks and reports trends on HAIs (Dudeck et al., 2015). According to El-Saed, Balkhy, and Weber (2013), the NHSN utilizes a benchmarking system to track facility HAI quality improvement efforts. The quality improvement efforts are measured utilizing risk-adjusted metrics (El-Saed et al., 2013). Risk-adjusted metrics are the stratification of reported hospital data (El-Saed et al., 2013). Reported CDI cases are represented by number of cases and measured using the Standard Infection Ratio (SIR) for benchmarking analysis.

The HAI reports are presented by the NHSN on an annual basis for state level and national level comparisons. El-Saed et al., (2013) state that approximately 90% of healthcare facilities across the nation report to the NHSN. The limitations of the NHSN HAI surveillances system include changes to the definitions, concepts, and reporting protocols which may impact the validity, consistency, and accuracy of the reported data. To mitigate this limitation, the NHSN ensures that facilities are informed of definition and reporting changes in a timely manner (El-Saed et al., 2013).

Kaiser Family Foundation Data Reports through the American Hospital Association. Data pertaining to ratio of hospital beds to population size and number of admissions per 1,000 persons was obtained from the AHA on the Kaiser Family Foundation Stata Facts data set. Health data and statistics reported to the Kaiser Family Foundation through the AHA is obtained from multiple sources such as private, public, and non-profit sectors. The data presented is not affiliated with Kaiser Permanente healthcare systems.

HCUP data reports through the AHRQ. The HCUP database contains secondary administrative data reported by organization partnerships through AHRQ. According to AHRQ (2014) administrative data is commonly used in studies regarding healthcare because collected healthcare data is more representative of the population than medical record data and hybrid data. To standardize data use, coding, and interpretation across the nation, participating healthcare facilities employ health information specialists to manage data coding systems that are nationally accepted. Using private health offices or independent physicians for coding may result in coding and interpretation practices that are not in alignment with national coding protocols and systems; thus, risking conflict with validation of data (AHRQ, 2014).

Quality improvement officers and HCUP personnel validate organization reporting and use of healthcare data through collaborations with key project contractors (AHRQ, 2008). Vendors and organizational stakeholders that participate in data collection and reporting go through a selection criterion that involves participant goals, statement of need, experience, and costs (AHRQ, 2014). The validation of data, data reporting, and coding is also critical for auditing and financial purposes (AHRQ, 2014). AHRQ collaborates with the Joint Commission, National Committee on Quality Assurance (NCQA), and CMS to validate accuracy and appropriateness of data. For example, data reviewed by CMS requires a re-abstraction agreement of 80% or more to confirm validation of data (AHRQ, 2014).

Operationalization of Constructs, Independent Variables

Acute care facility. A specific type of hospital facility that provides a wide range of specialty services such as trauma care, emergency care, and urgent care etc. (Hirshon et al., 2013). The main purpose of an acute care facility is to provide diagnostic, treatment, preventive, and curative services with regards to time-sensitivity and individuality of cases (Hirshon et al., 2013). NHSN obtains reports from acute care facilities for HAI risk-adjustment metrics and quality improvement benchmarking. (El-Saed, 2013). Because New Mexico is a state with a limited number of healthcare facilities, acute care and community healthcare facilities have been categorized under this variable category as some facilities that have reported to NHSN have been identified as community healthcare facilities. Long term healthcare facilities, mental health institutions, and rehabilitation facilities have been excluded from analysis. Acute care facilities are measured as nominal data. For protection of identification due to the small sample size of the population, this variable was represented under "hospital service line".

Admission year. This defines the time in which the patient was admitted to a facility. This variable was used to investigate the CDI diagnosis trend in a given year. The admission year was identified as an ordinal variable.

Age. Age is a variable categorized as continuous and a ratio rather than nominal, interval, or ordinal. Age was used to identify trends in its relationship to CDI incidence risk. HCUP reported this variable as individual (rather than categorical) values. For the purpose of this study and the statistical analysis methodology, the ages were recoded into groups.

Gender. In HCUP, this variable is coded as "Female" and assigned a numerical code (0=male, 1=Female). This variable was measured as a binary, categorical variable.

Hospital services lines. This term pertains to the specialty and types of medical and health services provided by a hospital facility. Examples of services include trauma, cardiac, and intensive care units. The types of services a hospital provides determines the overall hospital charges. This variable has been coded numerically and was measured as a nominal variable.

Length of stay. This variable was measured as a continuous variable as it is ratio-based. The length of stay was identified per case in HCUP. Length of stay was calculated by computing the total discharge days and number of discharges in a month (American Health Information Management Association [AHIMA], 2018).

Median household income quartiles. The HCUP database defines this variable as the median income among households for the state. The state of New Mexico has divided the quartiles into four income groups. The income ranks from the lowest average income (first quartile) to highest average income (last quartile). Each year presents a slightly different income range than the year before it, according to reports from Claritas (HCUP, n.d.). Because the data sets from 2014 and 2015 are combined, the variables will be represented by the following information derived from HCUP:

Table 1

Table of Income Ranges for Annual Median Household Income State Quartile Variable

Rank (Lowest to Highest Income)	Quartile/Percentile	Year	Income Range ($)
First	0-25th Percentile	2014	1-39,999
First	0-25th Percentile	2015	1-41,999
Second	26th-50th Percentile	2014	40,000 - 50,999
Second	26th-50th Percentile	2015	42,000 - 51,999
Third	51st to 75th Percentile	2014	51,000 - 65,999
Third	52nd to 75th Percentile	2015	52,999 - 67,999
Fourth	76th to 100th Percentile	2014	66,000 <
Fourth	77th to 100th Percentile	2015	68,000 <

Source. Median Household Income State Quartile information derived from HCUP

Number of diagnoses. This is the number of additional diagnoses, or comorbidities, that are present in addition to a primary diagnosis. These diagnoses are medical conditions, often chronic, that can occur in a combination similar to or different from the primary condition (Meghani et al., 2013). The term was first developed and used by clinician Alvan R. Feinstein in 1970 (Keezer & Sander, 2016) and is used interchangeably in health literature as co-existing or co-occuring conditions (Meghani et al., 2013). The two terms have slightly different meanings to number of conditions and their relation to the primary diagnosis.

Payer (insurance) type. This is categorized into six common insurance-type categories; specifically, it is the primary insurance that a patient used for medical services according to HCUP (HCUP, n.d.).

Race. In the HCUP database, race was identified as nominal data and characterized by numerical assignment. There are six race categories in the HCUP New Mexico data set.

Socioeconomic status. This is defined as the relationship among an individual's social and economic standing and health status (Baker, 2014). Higher social and economic standing has a strong correlation with a more positive health status (Baker, 2014). Income, education level, and occupation are common indicators of socioeconomic standing, according to Kangovi et al. (2013) and Berzofsky et al. (2014). Kangovi et al. (2013) mention that insurance status correlates with socioeconomic status as well as the type of healthcare services available per insurance type. The type of measurement that this variable fall under is categorical on a nominal scale.

Operationalization of Constructs, Dependent Variables

Clostridium difficile infection. CDI is a bacterial infection of the colon. It is contagious as it can be transmitted from a contaminated surface to an individual (CDC, 2015). CDI is also closely associated with high antibiotic use (CDC, 2015). Because of these factors and most of the cases occurring in healthcare environments, it is typically considered a Hospital Acquired Infection (CDC, 2015). CDI is a nominal variable that was identified under the ICD 9 and 10 codes and was measured against other variables such as socioeconomic characteristics and hospital service line type.

Data Analysis Plan

The data obtained from the HCUP New Mexico SID data set underwent analysis utilizing Statistical Package for Social Sciences (SPSS) software program that is used to analyze data for interpretation of research hypothesis pertaining to the social sciences (Ozgur, Kleckner, Li, 2015). SPSS was developed by IBM in 1968 (Ozgur et al., 2015). SPSS is utilized in a number of disciplines for different statistical analysis purposes.

Prior to using SPSS for the data analysis in this study, the data was transferred from the HCUP DVD files to Microsoft Excel for cleaning and screening; any variable that contained missing data or contained a cell size less than 10 was excluded from the data pool. Upon cleaning and screening, data was entered in SPSS for the analysis of the variables pertaining to the three research questions. Each research questions regarded a different statistical test based on the null hypothesis and variable category. Below are restatements of the research hypotheses with their associated statistical tests.

Restatement of the Research Hypotheses

RQ1: What is the association between patient characteristics (gender, age, race, number of diagnoses, length of stay) and hospital-acquired CDI diagnoses?

$H_0$1: There is no significant association between patient characteristics and CDI diagnoses.

H_a1: There is a significant association between patient characteristics and CDI diagnoses.

Selection of the statistical analysis test for Q1. There were multiple variables of interest in this first research hypothesis as multiple patient characteristics and their association with CDI rate was observed. A binary logistic regression model is appropriate for the statistical analysis of this hypothesis. A binary logistic analysis test allowed for the observation of odds and probabilities of multiple predictor variables against a dichotomous dependent variable (Sperandei, 2014). Each covariate was analyzed independently. After reviewing the results from each analysis, a collective summary was presented examining whether the covariates reveal a statistical significance in association with CDI diagnosis.

A binary regression model posits that the probability or odds that an outcome variable reveals a statistically significant relationship to predictor variable is by chance (Sperandei, 2014). The patient characteristics, for example gender, insurance type, age group, and race are nominal clusters and are identified as predictors of the presence of CDI diagnosis. Because these variables cannot fall within a scale of $-\infty$ and $+\infty$ as they are categorical in nature as they can only fall under the assumption that the outcome variables will be binary (Sommet & Morseilli, 2017). The results of the analysis were interpreted as an odds ratio, which is standard for any logistic regression model (Austin & Merlo, 2017).

RQ2: What is the association between socioeconomic characteristics (insurance type and income group) and hospital-acquired CDI diagnoses?

$H_0 2$: Socioeconomic characteristics have no significant association with CDI diagnoses.

H_a2: Socioeconomic characteristics have a significant association with CDI diagnoses.

Selection of the statistical analysis test for RQ2. This second research hypothesis concentrates on two socioeconomic groups—insurance (payer) type and median household income state quartile. Each variable was classified as a categorical variable. Since the insurance and income independent variables was analyzed as a correlation against the dependent variable CDI diagnosis, a binary logistic regression analysis was the appropriate statistical measure. The results were interpreted as an odds-ratio (Hidalgo & Sperandei, 2014).

RQ3: What is the association between acute care hospitals characteristics (service lines) and hospital-acquired CDI diagnoses?

H_03: Acute care hospital characteristics have no significant association with CDI diagnoses.

H_a3: Acute care hospital characteristics have a significant association with CDI diagnoses.

Selection of the statistical analysis test for RQ3. The third research hypothesis observed the predictability that hospital service lines have a positive correlation with CDI diagnosis using a binary logistic regression model. This research hypothesis also assumed that the outcome of the analysis was binary in nature, as the dependent variable (CDI diagnosis) was dichotomous and the independent variables (hospital service lines) were categorical, nominal variables. Such were noted assumptions to selecting this analysis method, according to Austin and Merlo (2017). The outcome variable for analysis of the covariates was an odds-ratio interpretation.

Threats to Validity

The trustworthiness of data for data analysis and research experimentation was warranted by reviewing and eliminating the threats to validity. Henderson, Kimmelman, Ferguson, Grimshaw, and Hackman (2013) identified and discussed three types of threats that impact the validity of a research experiment. Some threats to validity among the three can be influenced by the experimenter such as selection bias. Others are influences by outside forces such as unforeseen circumstances or factors that cannot be controlled.

Internal Threats to Validity

Internal validity threats are those that present a conflict of study outcomes with study variables influenced by the experimenter (Henderson et al., 2013). In this study, a possible threat to internal validity includes the type of testing instrument used. The SPSS software used for the statistical analysis of the study variables was ensured to be current and permissible for use in data analysis. As mentioned in the previous section, non-random sampling presented as a risk for selection bias. The intended sampling of the participants in the sampling frame was purposive due to the small population size and the need to observe specific population characteristics and variables to fulfill the research questions. Participants have been de-identified and regrouped as needed to protect identity and reduce the possibility of selection bias.

External Threats to Validity

External threats to validity are unexpected factors that skew or jeopardize the outcome of the experiment (Henderson et al., 2013). These types of threats are sometimes out of the control of the experimenter (Henderson et al., 2013). Possible occurrences of threats to external validity in this study is selection bias. Reduction of selection bias from purposive, non-random sampling is summarized in the previous paragraph and under the "Sampling Design" section.

Construct Threats to Validity

Constructs validity defines how the research experiment is generalizable of the population (Henderson et al., 2013). When a threat to construct validity is present in a research experiment, it indicates that the theoretical relationship between the experiment and worldly phenomenon is questioning and perhaps mischaracterized (Henderson et al., 2013). Henderson et al. (2013) mentioned generalizations of research variables and factors as examples of threats to construct validity by mischaracterization. In this study, generalizations of study variables such as terminology use (i.e. poor versus rich, kids and adolescents, hospitals) have been represented with more descriptive and definable terminology or descriptors (i.e. socioeconomic status, age groups, healthcare facility type). This was due to the differences in cultural and societal implications and interpretation of generalized terminology and concepts. Using specific identifiers present in peer-reviewed research, credible publications, and HCUP data reviewed by AHRQ were used to provide descriptive identification of study variables and concepts to avoid mischaracterization and generalization of study constructs. Other means for reducing threats to construct validity included triangulation of data which is the act of comparing research study constructs with other credible sources to ensure standardization of information.

Ethical Considerations

Ethical procedures and concerns were taken into consideration when requesting, reviewing, and analyzing secondary data for this study. As previously mentioned, secondary data pertaining to CDI incidence and hospital and patient characteristics of the New Mexico population was obtained, with permission, from HCUP. Prior to requesting data from HCUP, a data use agreement document was reviewed, acknowledged, signed, and returned to HCUP. Proper data use and privacy included the following terms (HCUP, 2014): 1) Data may not be shared by individuals who did not submit a data use agreement; 2) no person's or individual entities are to be disclosed in any way that violates the privacy and protection of individual identities; 3) Data must be properly discarded upon completion of use; 4) Data with cell size less than ten may not be presented in publications; 5) Individual establishments may not be contacted directly for confirmation of information presented in the data set and; 6) Acknowledgement of compliance, terms, and responsibilities for data use.

As the data reviewed was secondary data, there were no encounters with participant withdrawal or refusal to participate. However, data that was subject to risk of identification or insufficient for proper analysis was removed from the study. Data presented in the HCUP New Mexico Statewide Inpatient Data was aggregate and de-identified and recoded to protect patient and establishment identities. All information presented in this study from the data set was anonymous to prevent tracking or purposeful identification from outside stakeholders and reviewers of the study. Data was reviewed only by the requestor who signed the data use agreement on a private computer in an encrypted DVD. Completed use of the data will be returned to HCUP for destruction. IRB approval has been granted for this study (12-19-18-0564415).

Section 3: Presentation of the Results and Findings

Introduction

This study examined whether the cause of CDI rise in New Mexico between 2013 and 2015 was influenced by hospital and patient factors. Such factors served as the basis for the development of three research hypothesis that examined the relationship between CDI and hospital characteristics, CDI and socioeconomic characteristics, and CDI and patient characteristics. The analysis for each of the research questions was grounded on a quantitative approach. This chapter explores the variables analyzed, procedures for analysis of the hypotheses, results, and interpretation.

Data Collection of Secondary Data

Data Collection Source

The data included in this study were derived from the Healthcare Cost and Utilization Project (HCUP) New Mexico Statewide Inpatient data set. The selected years for the analysis were 2014 and 2015 which were obtained as two separate data sets. Though secondary data allows for the analysis of data already collected administratively, it was without risk of discrepancies. Some possible discrepancies that can appear in secondary data include missing data, incorrect reporting, and bias. The New Mexico HCUP was collected and screened for such discrepancies and the Agency for Healthcare Research and Quality (AHRQ) reviewed secondary data for validity and quality of information before it was released to HCUP for research study use.

Inferential Statistics

The demographic population included the hospitals and patients in New Mexico. To yield an accepted sample size, the 2014 and 2015 data set was combined in SPSS. The total number of participants in the data set was 327,562 (with the exclusion of missing data and the combination of the two data sets). After further data cleaning, the total participant included in the analysis equaled 186,669 (cases lest than a count of 10 were excluded; cases with individuals under the age of 18 were excluded; cases from maternal and mental health service lines were excluded). Based on the application of the G*Power logistic regression test and the combination of the two data sets, the minimum sample size was 778 (given the following: odds ratio = 1.5, alpha = 0.05, power = 8); an a priori method was implemented. The participants included hospital, socioeconomic, and patient characteristics.

Inferential statistics was applied in SPSS using the univariate analysis test to obtain the mean, median, minimum and maximum value of the data set for age and length of stay (LOS) variables after testing for normality of distribution. Number of diagnosis on record was analyzed with the same statistics. Univariate analysis for race, CDI diagnosis, number of diagnoses, payer type, hospital service line, and median household income state quartile [Table 2, Table 3] was conducted as a test for proportions as these variables are discrete and categorical in nature. Missing data and extreme values were excluded.

Table 2

Descriptive Characteristics for Continuous Variables

Variables	Mean	Media	Min	Max.
Age in years at Admission	62.34	64	18	103
Length of Stay (LOS)	4.5	3	0	22

Table 3

Descriptive Characteristics for Categorical Variables

Variables	Categories	Frequency	Percent
CDI Diagnosis	CDI Diagnosis	3367	1.8
	No CDI Diagnosis	183302	98.2
Age Group	(18 – 28yrs)	10222	5.5
	(29 – 38yrs)	13146	7
	(39 – 48yrs)	17937	9.6
	(49 – 58yrs)	30118	16.1
	(59 – 68yrs)	38632	20.7
	(69 – 78yrs)	37888	20.3
	(79 – 88yrs)	29025	15.5
	(89 – 98yrs)	9396	5
	(> 99yrs)	305	0.2
Gender	Male	89108	47.7
	Female	97561	52.3
Hospital Service Line	Injury	13660	7.3
	Surgical	48254	25.9
	Medical	124755	66.8
Median Household Income Quartile Groups *	First Quartile	48998	26.2
	Second Quartile	45488	24.4
	Third Quartile	52640	28.2
	Fourth Quartile	39543	21.2

Number of Diagnoses	(0 Diagnoses)	508	0.3
	(1-3 Diagnoses)	11299	6.1
	(4-6 Diagnoses)	25981	13.9
	(7-9 Diagnoses)	33306	17.8
	(10-17 Diagnoses)	74673	40.0
	(18 Diagnoses)	40902	21.9
Payer Type	No Charge	716	0.4
	Other	5622	3
	Self-Pay	6058	3.2
	Medicaid	35042	18.8
	Private Insurance	35046	18.8
	Medicare	104185	55.8
Race	Asian or Pacific Islander	1389	0.7
	Black	3727	2
	Other	4600	2.5
	Native American	15188	8.1
	Hispanic	57783	31
	White	103982	55.7

Note. For *Median Household Income Quartile* definitions, refer to *Definition of Constructs*.

Confounders

When controlling for confounders, age group and gender were taken into consideration. Adjusting the analysis for age and gender was modeled by Eze, Balsells, Kyaw, and Nair (2017) which discuss the presence of age and gender as potential confounding variables. Gender and age were tested against all variables in the research questions to test for any confounding conflicts with CDI diagnosis outcomes. A logistic regression analysis was performed to determine changes to the odds ratio for each variable while controlling for age and gender

Analysis of Hypotheses

Research Question 1

RQ1: What is the association between patient characteristics (gender, age, race, number of diagnoses, length of stay) and hospital-acquired CDI diagnoses?

$H_0$1: There is no significant association between patient characteristics and CDI diagnoses.

H_a1: There is a significant association between patient characteristics and CDI diagnoses.

For the analysis of this research question, each covariate was analyzed independently utilizing the binary logistic regression analysis. The variable for CDI diagnosis served as the dependent variable while gender, age, race, number of diagnoses, and length of stay served as the independent variables (each variable was analyzed independently for association with CDI). The outcome variable is CDI diagnosis. The statistical significance and testing of the hypothesis for this research question was determined by interpreting the overall outcome of the covariates.

Gender. A binary logistic regression analysis to investigate the association between gender and CDI diagnosis was conducted [Table 4]. The predictor variable, gender was tested a priori to verify there was no violation of the assumption of the linearity of the logit. The predictor variable, gender, in the logistic regression analysis was found to contribute to the model. The variable Male served as the reference variable.

The unstandardized Beta weight for the predictor variable female gender: B = [0.270],],

Wald = [58.479], $p < .001$. The estimated odds ratio favored an increase of nearly 31% [Exp (B) = 1.310, 95% CI (1.223, 0.404)] for CDI diagnosis for risk in females compared to males. When accounting for confounders age and race, no significant change in risk level was observed [Table 5].

Table 4

Binary Logistic Regression for Gender

Variables	B	Wald	Exp(B)	95% C.I.for EXP(B)		Sig.
				Lower	Upper	
Gender						
Female	0.27	58.479	1.31	1.223	1.404	0.000

Table 5

Binary Logistic Regression for Gender, Adjusted with Covariates

Variables		B	Wald	Exp(B)	95% C.I.for EXP(B)		
					Lower	Upper	Sig.
Gender							
	Male (ref.)			1.000			
	Female	0.251	49.934	1.285	1.199	1.377	0.000
Race							
	White (ref.)			1.000			
	Black	-0.116	0.697	0.890	0.677	1.170	0.404
	Hispanic	-0.152	13.082	0.859	0.792	0.933	0.000
	Asian and Pacific Islander	-0.377	2.367	0.686	0.424	1.109	0.124
	Native American	0.559	102.753	1.748	1.569	1.948	0.000
	Other	-0.090	0.535	0.914	0.718	1.163	0.465
Age Categories (in years)							
	18-28 (ref.)			1.000			
	29-38	-0.194	2.475	0.824	0.647	1.049	0.116
	39-48	0.017	0.023	1.017	0.819	1.263	0.879
	49-58	0.167	2.743	1.182	0.970	1.440	0.098
	59-68	0.334	11.827	1.397	1.155	1.690	0.001
	69-78	0.599	39.248	1.820	1.509	2.196	0.000
	79-88	0.614	39.635	1.848	1.527	2.238	0.000
	89-98	0.662	34.953	1.938	1.556	2.413	0.000
	>99	-0.712	0.992	0.491	0.121	1.993	0.319

Age. A second binary logistic regression analysis was conducted to investigate the association between age group and CDI diagnosis [Table 6]. Age was divided into nine groups in increments of 10 years ([18-28], [29-38], [39-48] …). This recoding approach was modeled by other research publications that have taken a similar approach to observe different patterns of age groups and association with CDI (Pechal, Lin, Allen, & Reveles, 2016; Sandberg, Davis, Gebremariam, & Adler, 2015).

These age groups have been coded into one variable called AGEGROUP. The predictor variable, age group was tested a priori to verify there was no violation of the assumption of the linearity of the logit. The predictor variable, age group, in the logistic regression analysis was found to contribute to the model. The unstandardized Beta weight for the predictor variable age group: B = [0.134], Wald = [178.182], p < .001. The estimated odds ratio for CDI diagnosis presented and increase of nearly 14% [Exp (B) = 1.144, 95% CI (1.121, 1.166)] for every ten-year increase in age.

Table 6

Binary Logistic Regression for Age Group

Variables		B	Wald	Exp(B)	95% C.I.for EXP(B)		Sig.
					Lower	Upper	
Age Group							
	AGEGROUP	0.134	178.182	1.144	1.121	1.166	0.000

Race. A binary logistic regression analysis to investigate the association between race and CDI diagnosis was conducted for the third covariate regarding patient characteristics [Table 7]. The predictor variable, race was tested a priori to verify there was no violation of the assumption of the linearity of the logit. The predictor variable, race, in the logistic regression analysis was found to contribute to the model. The racial group White served as the baseline variable for this analysis. The predictor variables for the racial group Native American had a greater propensity to CDI diagnosis than the other racial groups with the unstandardized Beta weight [Exp (B) = [1.511], Wald = [57.945]]. However, being Hispanic showed a decreased likelihood of CDI diagnosis by 78% [Exp(B) = [0.783], SE = [0.041], Wald = [35.052]] compared to other races. Black, Asian and Pacific Islander, and other races presented with no statistical significance to an association with CDI diagnosis.

Table 7

Binary Logistic Regression for Race

Variables		B	Wald	Exp(B)	95% C.I.for EXP(B)		Sig.
					Lower	Upper	
Race							
	White (ref.)		129.294				0.000
	Black	-0.262	3.549	0.770	0.586	1.011	0.060
	Hispanic	-0.245	35.052	0.783	0.722	0.849	0.000
	Asian and Pacific Islander	-0.433	3.118	0.649	0.401	1.049	0.077
	Native American	0.413	57.945	1.511	1.358	1.680	0.000
	Other	-0.212	2.990	0.809	0.636	1.029	0.084

Number of diagnoses on record. A binary logistic regression was conducted for this variable [Table 8]. This variable was assessed to determine whether is served as a confounding factor in CDI diagnosis. The number of diagnosis on record indicates the number of conditions that the patient has in addition to CDI diagnosis. The correlation between the two was analyzed to assess the strength of the relationship.

The number of diagnosis on record served as the independent, predictor variable for the equation and was tested a priori to verify there was no violation of the assumption of the linearity of the logit. The predictor variable, number of diagnoses, in the logistic regression analysis was found to contribute to the model. The reference variable was a diagnosis total of 18, as it contains a greater participant pool. The predictor variable is a statistically significant predictor of CDI diagnosis [$p < 0.05$]. Having an additional one to three diagnosis apart from CDI increased the likelihood of CDI diagnosis by 4%; 96% less likely than having eighteen diagnoses [Table 8]. For diagnoses between four to six increased the likelihood by 13%; 77% less likely than having eighteen diagnoses [Table

8]. For every increased increments of diagnoses, the odds in likelihood of a CDI diagnosis increased significantly. However, having zero diagnoses on record apart from a CDI diagnosis presented a non-statistically significant association [p > 0.05] [Table 8]. Adjusting for the age and race covariates did not present as confounders significantly influencing CDI diagnosis [Table 9].

Table 8

Binary Logistic Regression for Number of Diagnoses (Grouped)

Variables		B	Wald	Exp(B)	95% C.I.for		Sig.
					Lower	Upper	
Number of Diagnoses							
	18 (ref.)		1397.136				
	0	-18.044	0.000	0.000	0.000	.	0.992
	1-3	-3.282	191.422	0.038	0.024	0.060	0.000
	4-6	-2.038	542.546	0.130	0.110	0.155	0.000
	7-9	-1.594	610.027	0.203	0.179	0.231	0.000
	10-17	-0.911	578.145	0.402	0.373	0.433	0.000

Table 9

Binary Logistic Regression for Number of Diagnoses (Grouped), Adjusted with Covariates

Variables	B	Wald	Exp(B)	95% C.I.for EXP(B)		Sig.
				Lower	Upper	
Number of Diagnoses						
18 (ref.)		1263.896				0.000
0	-17.984	0.000	0.000	0.000	.	0.992
1-3	-3.234	183.552	0.039	0.025	0.063	0.000
4-6	-1.986	497.157	0.137	0.115	0.163	0.000
7-9	-1.553	566.291	0.212	0.186	0.240	0.000
10-17	-0.894	551.052	0.409	0.379	0.441	0.000
Race						
White (ref.)		91.341				0.000
Black	-0.213	2.313	0.808	0.615	1.063	0.128
Hispanic	-0.132	9.881	0.876	0.807	0.951	0.002
Asian and Pacific Islander	-0.325	1.746	0.722	0.446	1.170	0.186
Native American	0.425	58.162	1.529	1.371	1.705	0.000
Other	-0.090	0.527	0.914	0.718	1.165	0.468
Age Categories (in years)						
18-28 (ref.)		47.942				0.000
29-38	-0.430	12.024	0.651	0.511	0.830	0.001
39-48	-0.413	13.657	0.662	0.532	0.824	0.000
49-58	-0.375	13.466	0.687	0.562	0.840	0.000
59-68	-0.305	9.479	0.737	0.607	0.895	0.002
69-78	-0.126	1.667	0.881	0.728	1.068	0.197
79-88	-0.184	3.373	0.832	0.684	1.012	0.066
89-98	-0.098	0.738	0.907	0.725	1.134	0.390
>99	-1.323	3.411	0.266	0.065	1.084	0.065

Length of stay. It was appropriate to perform the regression test to examine whether there exist a statistically significant association with CDI diagnosis and length of stay (LOS) as it is a patient characteristic. Prior to entering the LOS variable in the binary logistic regression test, using existing literature on LOS as a reference, the length of stay days calculated for this analysis is 0 to 22 days (Zhang et al., 2016). This was primarily adjusted to exclude extreme values not conducive to what is normally observed in healthcare research literature. Zhang et al. (2016) calculated the LOS at the national level. The odds of having a CDI diagnosis increases by approximately 14% for every extra day that a patient is hospitalized [Exp(B) = 1.138, Wald = 1882.346, CI 95% = (1.131 – 1.144)].

Table 10

Binary Logistic Regression for Length of Stay

Variables		B	Wald	Exp(B)	95% C.I.for EXP(B)		Sig.
					Lower	Upper	
Length of Stay							
	Length of Stay	0.129	1882.346	1.138	1.131	1.144	0.000

When adjusting the predictor variable LOS with the covariates age and race, there wasn’t a significant change in the odds of being diagnosed with CDI [Table 11]. The races Hispanic and Native American showed a statistically significant association to LOS and CDI diagnosis. Native Americans continued to show a greater likelihood of being diagnosed with CDI in relativity to LOS compared to Hispanics. Races that fell under the ‘other’ category had lesser odds of being diagnosed with CDI in relativity to LOS compared to Hispanics by 9%.

Table 11

Binary Logistic Regression for Length of Stay, Adjusted with Covariates

Variables		B	Wald	Exp(B)	95% C.I.for EXP(B)		Sig.
					Lower	Upper	
Length of stay							
	Length of stay	0.127	1761.023	1.135	1.128	1.142	0.000
Race							
	White (ref.)		106.115				0.000
	Black	-0.163	1.355	0.849	0.645	1.118	0.244
	Hispanic	-0.146	11.955	0.864	0.796	0.939	0.001
	Asian and Pacific Islander	-0.377	2.347	0.686	0.423	1.111	0.126
	Native American	0.449	64.758	1.567	1.404	1.748	0.000
	Other	-0.247	3.994	0.781	0.613	0.995	0.046
Age Categories (in years)							
	18-28 (ref.)		159.361				0.000
	29-38	-0.198	2.569	0.820	0.644	1.045	0.109
	39-48	-0.035	0.101	0.965	0.777	1.200	0.751
	49-58	0.067	0.436	1.069	0.877	1.304	0.509
	59-68	0.216	4.869	1.241	1.024	1.503	0.027
	69-78	0.466	23.421	1.593	1.319	1.924	0.000
	79-88	0.492	25.086	1.635	1.349	1.982	0.000
	89-98	0.600	28.382	1.821	1.461	2.271	0.000
	>99	-0.733	1.046	0.481	0.118	1.957	0.306

Research Question 2

RQ2: What is the association between socioeconomic characteristics (insurance type and income group) and hospital-acquired CDI diagnoses?

$H_0$2: Socioeconomic characteristics have no significant association with CDI diagnoses.

H_a2: Socioeconomic characteristics have a significant association with CDI diagnoses.

Payer (insurance) type. A binary logistic regression analysis to investigate the association between payer type and clostridium difficile diagnosis was conducted for the socioeconomic characteristic variable [Table 12]. The predictor variable, payer type was tested a priori to verify there was no violation of the assumption of the linearity of the logit. The predictor variable, payer type, in the logistic regression analysis was found to contribute to the model. The payer type group Medicare served as the baseline variable for this analysis. All payer groups presented as statistically significant in the association with CDI diagnosis as $p<0.05$ for all payer groups [Table 12]. The odds for users of Medicaid were 63% more likely to be diagnosed with CDI compared to other insurance users [Exp(B) = 0.630, Wald = 86.096, CI 95% (0.572 – 0.695)]. The odds for users with no charge had being diagnosed with CDI decreased by 82% [Exp(B) = 0.184, Wald = 8.553, CI 95% (0.059 – 0.572)] which is lower compared to Medicaid insurance users. Those who were not charged for services had a less likelihood of being diagnosed with CDI compared to other insurance groups.

The covariates Race and Age presented as significant confounders to the association between insurance use and CDI diagnosis [Table 13]. When factoring Race and Age into the regression analysis for the Payer Type variable, the odds of Payer Type prediction the likelihood of a CDI diagnosis increased. Being White, Hispanic and Native American showed a statistically significant association to Payer Type use and CDI diagnosis. Other races and all age groups were not statistically significant confounders.

Table 12

Binary Logistic Regression for Payer Type

Variables	B	Wald	Exp(B)	95% C.I.for EXP(B)		Sig.
				Lower	Upper	
Payer Type						
Medicare (ref.)		256.366				0.000
Medicaid	-0.462	86.096	0.630	0.572	0.695	0.000
Private Insurance	-0.611	133.467	0.543	0.490	0.602	0.000
Self-Pay	-1.140	55.696	0.320	0.237	0.431	0.000
No-Charge	-1.693	8.553	0.184	0.059	0.572	0.003
Other	-0.719	30.827	0.487	0.378	0.628	0.000

Table 13

Binary Logistic Regression for Payer Type, Adjusted with Covariates

Variables		B	Wald	Exp(B)	95% C.I.for EXP(B)		Sig.
					Lower	Upper	
Payer Type							
	Medicare (ref.)		91.599				0.000
	Medicaid	-0.279	18.809	0.757	0.667	0.858	0.000
	Private Insurance	-0.443	53.339	0.642	0.570	0.723	0.000
	Self-Pay	-0.882	31.157	0.414	0.304	0.564	0.000
	No-Charge	-1.466	6.396	0.231	0.074	0.719	0.011
	Other	-0.664	24.812	0.515	0.396	0.668	0.000
Race							
	White (ref.)		135.604				0.000
	Black	-0.123	0.782	0.884	0.673	1.162	0.377
	Hispanic	-0.150	12.707	0.861	0.792	0.935	0.000
	Asian and Pacific Islander	-0.333	1.840	0.717	0.443	1.160	0.175
	Native American	0.536	92.450	1.709	1.532	1.907	0.000
	Other	-0.055	0.198	0.947	0.744	1.205	0.657
Age Categories (in years)							
	18-28 (ref.)		37.852				0.000
	29-38	-0.235	3.640	0.791	0.621	1.006	0.056
	39-48	-0.044	0.155	0.957	0.770	1.190	0.694
	49-58	0.070	0.466	1.072	0.877	1.311	0.495
	59-68	0.133	1.672	1.142	0.934	1.398	0.196
	69-78	0.255	5.656	1.290	1.046	1.592	0.017
	79-88	0.266	5.946	1.305	1.054	1.616	0.015
	89-98	0.336	7.575	1.399	1.102	1.778	0.006
	>99	-1.020	2.026	0.361	0.088	1.469	0.155

Income. The variable is classified as the median household income state quartile meaning that the patient's zip code is a determinate of the income category specific to the state. A binary logistic regression was performed to analyze the association between income category and CDI diagnosis. Income quartile served as the predictor variable, which was tested for a priori and the variable was found to contribute to the model [Table 14]. The first quartile was designated as the indicator variable; the CDI diagnosis was the dependent variable. Only the income group from the fourth quartile presented a statistically significant association with CDI diagnosis [B = [-0.121], Wald = [5.612], (p < 0.05); all other income groups did not present as statistically significant predictors of CDI diagnosis. The income group in the fourth quartile were 88% less likely to be diagnosed with CDI compared to the income group in the first quartile. After factoring age and race as potential confounders, a significance in the association between income level and CDI diagnosis was identified. All quartile groups, except for the second quartile group, showed that age and race favored a decrease in the likelihood of a CDI diagnosis [Table 15]

Table 14

Binary Logistic Regression for Median Household Income Quartiles

Variables		B	Wald	Exp(B)	95% C.I.for EXP(B)		Sig.
					Lower	Upper	
Income							
	Median household Income First Quartile (ref.)		7.299				0.063
	Median household Income Second Quartile	-0.021	0.185	0.980	0.892	1.076	0.667
	Median household income Third Quartile	-0.083	3.127	0.920	0.840	1.009	0.077
	Median household Income Fourth Quartile	-0.121	5.612	0.886	0.801	0.979	0.018

Table 15

Binary Logistic Regression for Median Household Income Quartiles, Adjusted with Covariates

Variables	B	Wald	Exp(B)	95% C.I.for EXP(B)		Sig.
				Lower	Upper	
Income						
Median household Income First Quartile (ref.)		8.872				.031
Median household Income Second Quartile	-0.023	0.222	0.978	0.890	1.074	0.637
Median household income Third Quartile	-0.099	4.474	0.905	0.826	0.993	0.034
Median household Income Fourth Quartile	-0.128	6.264	0.880	0.796	.973	0.012
Race						
White (ref.)		146.830				0.000
Black	-0.123	0.780	0.884	0.673	1.162	0.377
Hispanic	-0.154	13.520	0.857	0.790	0.931	0.000
Asian and Pacific Islander	-0.369	2.262	0.691	0.428	1.118	0.133
Native American	0.553	100.375	1.738	1.560	1.936	0.000
Other	-0.106	0.748	0.899	0.707	1.144	0.387
Age Categories (in years)						
18-28 (ref.)		212.293				0.000
29-38	-0.198	2.600	0.820	0.644	1.044	0.107
39-48	0.014	0.016	1.014	0.817	1.259	0.900
49-58	0.159	2.500	1.173	0.963	1.429	0.114
59-68	0.332	11.705	1.394	1.153	1.687	0.001
69-78	0.603	39.812	1.828	1.516	2.205	0.000
79-88	0.626	41.143	1.870	1.544	2.264	0.000
89-98	0.696	38.773	2.006	1.611	2.498	0.000
>99	-0.654	0.835	0.520	0.128	2.113	0.361

Research Question 3

RQ3: What is the association between acute care hospitals characteristics (service lines) and hospital-acquired CDI diagnoses?

$H_0$3: Acute care hospital characteristics have no significant association with CDI diagnoses.

H_a3: Acute care hospital characteristics have a significant association with CDI diagnoses.

Hospital service line. The binomial logistic regression was conducted to examine the probability that hospital characteristics was strongly associated with CDI diagnosis. Characteristics observed in this analysis include the hospital service lines. The variable hospital service line was tested a priori to verify that the assumptions of the linearity of the logit were met [Table 16]. The covariate served as the predictor model in the logistic regression analysis. The variable group hospital service line contains three subgroups: medical, injury, and surgery. Medical served as the baseline variable for this analysis as it contained the largest number of cases.

Table 16

Binary Logistic Regression for Hospital Service Line

Variables		B	Wald	Exp(B)	95% C.I.for EXP(B)		Sig.
					Lower	Upper	
Service Line							
	Medical (ref.)		525.919				0.000
	Injury	0.696	24.040	2.005	1.518	2.648	0.000
	Surgical	1.740	168.427	5.696	4.380	7.407	0.000

The odds of being diagnosed with CDI in a surgery center was five times more likely compared to being in a medical service line [Exp(B) = 5.696, Wald = 168.427, CI 95% = (4.380, 7.407)]. In an injury service line, the odds of being diagnosed with CDI was two times more likely compared to medical service lines [Exp(B) = 2.005, Wald =

24.040, CI 95% = (1.518, 2.648)]. All service lines showed a positive association with CDI diagnosis. The covariates race and age had minimal to no impact on hospital service line as confounders [Table 17].

Table 17

Binary Logistic Regression for Hospital Service Line, Adjusted with Covariates

Variables		B	Wald	Exp(B)	95% C.I.for EXP(B)		Sig.
					Lower	Upper	
Service Line							
	Medical (ref.)		495.032				0.000
	Injury	0.701	24.229	2.015	1.524	2.663	0.000
	Surgical	1.714	162.875	5.549	4.265	7.220	0.000
Race							
	White (ref.)		147.417				0.000
	Black	-0.209	2.252	0.811	0.617	1.066	0.133
	Hispanic	-0.181	18.696	0.834	0.768	0.906	0.000
	Asian and Pacific Islander	-0.365	2.214	0.694	0.429	1.123	0.137
	Native American	0.534	93.222	1.705	1.530	1.900	0.000
	Other	-0.011	0.008	0.989	0.777	1.259	0.928
Age Categories (in years)							
	18-28 (ref.)		160.507				0.000
	29-38	-0.231	3.526	0.793	0.623	1.010	0.060
	39-48	-0.038	0.118	0.963	0.775	1.196	0.731
	49-58	0.109	1.170	1.115	0.915	1.360	0.279
	59-68	0.287	8.703	1.333	1.101	1.613	0.003
	69-78	0.522	29.681	1.685	1.397	2.033	0.000
	79-88	0.487	24.871	1.628	1.344	1.972	0.000
	89-98	0.519	21.467	1.681	1.349	2.094	0.000
	>99	-0.809	1.280	0.445	0.110	1.809	0.258

Conclusion

Preceding the analysis of each research hypothesis, all independent and dependent variables were cleaned and recoded. A univariate analysis was performed for each variable to assess for frequency and descriptive summary for each variable. A binary logistic regression was performed for all three research hypotheses. As the outcomes for each research hypothesis revealed statistical significance in the odds between patient characteristics, socioeconomic characteristics, and hospital characteristics. All three research hypotheses examined were accepted as predictors of CDI diagnosis; thus, rejecting the null hypothesis that there is no significant association between the characteristics and CDI diagnosis.

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

Discussion

The aim of the study was to determine whether hospital characteristics, socioeconomic characteristics and patient characteristics influence presence of an increased CDI incidence in New Mexico. Between the years of 2014 and 2015, New Mexico has encountered an increase in CDI incidence (diagnosis) compared to the national average, according to the National and State Healthcare Associated Infections Progress Report (CDC, 2015; CDC 2016). Also, it is one of the few states that have seen a growth in CDI incidence compared to most states which have displayed a decrease in CDI incidence within the same time frame. Other research literature has examined factors such as hospital teaching status, antibiotic use, and antimicrobial stewardship practices. However, little research exists in whether socioeconomic characteristics, service line, and associated patient characteristics play a role in CDI incidence. The study findings will answer the question of whether these factors have a strong relationship to CDI incidence and if such factors present as a health disparity among New Mexico populations in relativity to CDI diagnosis.

Key Findings

Patient Characteristics

Age. The first research question explored the association of patient characteristics with CDI diagnosis. The following patient characteristics were observed: age, gender, insurance type, and race. Number of diagnosis was also included. Age showed a significant association between those with a CDI diagnosis and those without a CDI diagnosis. The average age of participants was 62 years; the youngest and highest adult age examined was 18 and 103 years, respectively. For every ten-year increase in age, the odds of being diagnosed with CDI increased by 14%. This was congruent with the research literature that older age has a strong correlation with the likelihood of a CDI diagnosis. The population of individuals with a CDI diagnosis was older than the mean of all the study participants.

Gender. Gender analysis in relativity to CDI diagnosis was conducted as a binary logistic regression test to observe the independence of male and female participants and the association with CDI diagnosis. The analysis served the purpose of determining whether one gender has a stronger association with CDI diagnosis than the other. If there was a greater difference between the two genders, then the association between genders plays a significant role in likelihood of CDI diagnosis. The result of the binary logistic regression analysis concluded that a significant association between gender and CDI diagnosis is present. Females have 31% odds of being diagnosed with CDI compared to males. However, when age and race was factored as confounders, the likelihood of being a female and diagnosed with CDI decreased by 12%. Being between the ages of 59 to 98 years of age and of Native American race had a greater propensity to CDI diagnosis. The 12% decrease may indicate that the individuals not within the 59 to 98 age range and Native American race are a greater population among females in comparison.

Race. The binary logistic regression analysis was implemented to explore the relationship between race and CDI diagnosis. Five racial groups were examined: White, Black, Hispanic, Native American, Asian and Pacific Islander, and Other. The racial group White served as the baseline as it had the highest number of cases. There was a significant association between race and CDI diagnosis, based on the p-value being less than the alpha (0.05) except for the Asian and Pacific Islander group, which had a p-value greater than the alpha (0.05); Black and Other also had a p-value greater than the alpha.

The Native American and Hispanic racial group present with a statistically significant relationship to CDI diagnosis. Specifically, the Native American race, has a stronger tendency towards the likelihood of having a CDI diagnosis compared to the White, Black, Asian, Hispanic, and Other racial groups. Interestingly, Hispanics showed a decrease in the likelihood of being diagnosed with CDI compared to other groups. There was no statistically significant association between the Black and Asian and Pacific Islander ethnic groups. For some of the analyses of other variables in, the ethnic group ‘Other’ either presented as a statistically significant confounder or a non-statistically significant confounder. This may suggest that race groups in the ‘Other’ category may be impacted by other variables (i.e. payer type) that determine their access to health resources and exposure to CDI.

Number of diagnoses. The number of diagnosis presented a statistically significant relationship to CDI diagnosis. As there was a statistically significant association with CDI, it would suggest that the number of diagnoses increased the probability of length of stay, antibiotic use, comorbidities, etc. which are factors related to CDI incidence and number of diagnosis (Balch, Wendelboe, Vesely, & Bratzler, 2017). However, when accounting for potential confounders, age and race, there was little to no statistical significance in the association between number of diagnoses and

CDI diagnosis. It is possible that the diagnoses associated with age and gender do not have an influence on or by CDI.

Length of stay. Length of stay showed a significant association with CDI diagnosis as indicated by the odds of the binomial logistic regression. For every increase in length of stay in the hospital, the likelihood of being diagnosed with CDI increases by 14%. This suggest that hospitals that had patients with longer lengths of stay than most hospitals have a strong association with the number of CDI diagnosis (CDI rate). Minimal effect on length of stay was observed when factoring age and race as potential confounders.

Whites showed a greater risk of CDI compared to non-Whites such as Blacks (Argamany et al., 2016) and Asians (Mao et al., 2015) which presents a congruency of the evidence in literature and the findings of this study. Length of stay and race combined express an increased risk of CDI diagnosis which is supported by Argamany et al. (2016) but refuted by Mao et al. (2015). Native Americans, however, have higher odds of being diagnosed with CDI compared to Whites, though the length of stay is shorter than Whites. Though, having shorter length of hospital stay can be a preventive factor for acquiring CDI in the hospital setting, the study findings propose that quality of service could be the contributing factor for the higher number of CDI diagnosis among Native Americans. This is synonymous to the study findings in the regression analysis for insurance type use and adjustment for race.

Socioeconomic Characteristics

Median household income state quartile. The relationship between income and CDI diagnosis was analyzed with the implementation of the binomial logistic regression. Similar to the insurance (payer) type variable, the income variable was divided into four categories: first quartile, second quartile, third quartile, and fourth quartile. Each quartile was a representation of an income range; the first quartile represented the highest income range and served as the baseline variable while the fourth quartile represented the lowest income range. Both independent regression analysis and the inclusion of potential confounders age and race, the income groups except the second quartile, presented a statistically significant association with CDI diagnosis. This was in tandem with the literature that have identified similar observations (Miller et al., 2016; Olanipekun et al., 2016; & Becerra et al., 2015). However, Bakullari et al. (2014) and Argamany et al. (2016) mention that income level does not significantly influence odds of being diagnosed with CDI among races, which the findings in this study refute as this study illustrates that risk levels are likely to differ significantly when factoring race in the regression analysis of income.

Insurance (payer) type. The binary logistic regression analysis was performed to explore the relationship between insurance payer type and CDI diagnosis. The insurance types were divided into the following: Medicare, Medical, private insurance, self-pay, no charge, and other. Medicare served as the baseline as it had the highest number of cases. A significant association was observed between insurance types and CDI diagnosis as the p value was less than (0.05) and the odds for all insurance types were less than one. All insurance types have a strong relationship with CDI diagnosis; Medicaid holders have a greater propensity towards CDI diagnosis than other insurance types; especially when compared to Medicare users. Although the odds of Medicaid users being diagnosed with CDI decreased by 37%, other insurance types showed a greater decrease in the odds of a CDI diagnosis.

When adjusting the regression with the addition of age and race as potential confounders, the odds among all insurance types decreased significantly. Therefore, age and race were significant confounders in the regression analysis for insurance type. Individuals between the ages of 69 and 98 years of age and of Native American descent, had the highest odds of being diagnosed with CDI.

Reveles et al (2014) and Kassam et al. (2016) support the findings of Medicaid users having a strong association with CDI diagnosis, secondary to Medicare. Insurance type is dependent on hospital location and quality of services (Weissman et al., 2013). The result of Native Americans still presenting with higher odds may suggest the quality of care and location of care they are receiving. Further research on the association between race, income level, insurance, and quality of patient care is recommended as it might provide additional insight on health disparities and disease prevention. It could likely explain the higher risk of patients under this insurance plan being diagnosed with CDI compared to other insurance plans (used as primaries).

Hospital Characteristics

Hospital service line. A binomial logistic regression analysis was performed within the same test as the LOS to assess the significance of the association between hospital service line and CDI diagnosis. Maternal and mental health service lines were excluded from the analysis as they are not variables relevant to the study. The outcome of the test indicated that a significant relationship was present between hospital service line (injury, surgical, and medical) and CDI diagnosis.

All three variables showed a significant correlation to length of stay and CDI diagnosis. In regard to the strength of the relationship to each service line and CDI diagnosis, all three service lines showed a strong relationship with surgery service lines having the most positive relationship with CDI diagnosis. This aligns with the literature in that, patients admitted to a surgical unit have a greater risk of surgical site infections and the use of antibiotics, frequent interaction between clinical staff, and longer hospital stays, which presents with a strong linear relationship to CDI risk (Guh et al., 2017; Li et al., 2016; Flagg et al., 2014).

Alignment with the Theoretical Framework

The Fundamental Cause Theory explores the differences in health opportunities, barriers, and norms across various socioeconomic and sociodemographic groups. Observing such differences allow for the identification for disparities and the factors from these different groups that influence the presence of disparities. Race and number of diagnosis between patients are sociodemographic factors that presented with disparate variations in CDI diagnosis. Hispanics had the greatest likelihood of CDI diagnosis in comparison to other races. Although does not align with the existing literature that factors such as lack of access to antibiotic therapy and longer length of stay were contributors to

CDI diagnosis, it does prompt for further research on the role of race and CDI incidence risk.

The outcome of the findings for race, however, do provide an illustration of the social gradient and differences that link to CDI risk. For instance, Native Americans and individuals with longer length of stays in hospitals had a greater likelihood of a CDI diagnosis than those who are of other ethnic groups and shorter length of stay. There is some evidence of a health disparity among the latter of the socioeconomic and sociodemographic group, even though the likelihood of a CDI diagnosis is much lower. Because there is a significant difference between such groups the outcome of health aligns with the foundation of the Fundamental Cause Theory.

The Pathways Community Model centers on the idea that distal causes of health and the presence of health disparities share a mutual relationship. This is observable in the payer type used by patients, the services a hospital provides, and the likelihood of a CDI diagnosis and whether there exists a difference among the groups. The type of insurance provides information on what type of services a patient receives. This may serve as an indicator on the resources and services available for CDI prevention and management. According to Arora et al. (2013), insurance payer groups provide a basis of financial provisions that a hospital can utilize for its services. For example, if a hospital acquires more self-payers than Medicare payers, the self-payers may cover more services in the hospital than Medicaid payers. Therefore, patients that attend a hospital that has more self-payers than Medicaid payers may be attending an environment that may have more resources for preventing and managing CDI than a hospital that has more Medicaid payers.

A similar example can be applied to hospitals with different service lines. The types of service-lines that a hospital provides can provide some indication of financial resources and the services and resources available for programs that prevent or manage CDI. As insurance and service-line are not direct causes of CDI diagnosis in patient, per the framework of the Pathways Model, the variables serve as distal causes of health and health disparities. In the outcome of the analysis, both variables were found to be significantly associated with CDI diagnosis. More specifically, Medicaid users and hospitals with surgical service-lines presented with the greatest odds of CDI diagnosis among the population.

Limitations

Secondary data collected from HCUP may not be an exact representation of the population data since the coding was completed administratively. Not all facilities have the same data collection tools and protocols. Validity and reliability of data was reviewed by the NCQA, the Joint Commission, the AHRQ, and CMS for accuracy of data prior to distribution for research use. The data reviewed for this study pertains only to the state of New Mexico and is not a national representation of CDI diagnosis and associated variables.

Teaching and non-teaching status and bed size was not included in this study as it was not a defined variable in the HCUP data set. Therefore, differences in number of CDI cases due to hospital size will not be reflected and may impact representation of number of CDI cases per facility and incidence rate. Antibiotic use, a potential confounder present in extensive CDI literature and professional publications, was excluded from analysis as it was not available in the HCUP data set. New Mexico excluded variables such as hospital jurisdiction and identifiers in the HCUP data set. This information was not incorporated into the study for hospital location analysis and CDI diagnosis association analysis.

Recommendations for Further Research

As literature on hospital jurisdiction and HAIs exist, this should be further reviewed for the state of New Mexico. Bed size and antibiotic prescribing practices should also be observed in conjunction to CDI diagnoses and incidence rate in New Mexico acute care facilities. This will provide researchers with the opportunity to explore the relationship between CDI diagnoses, antibiotic prescribing practices, and bed size in terms of resource allocation, financial implications, and infectious disease control and management practices for CDI. Further studies should also investigate CDI incidence rate and SSRIs for specific communities throughout New Mexico as this study only reviewed the presence of a CDI diagnosis. The methods of research that were applied to this study and the recommendations in the observation of other variables in this study can be applied to the research of similar epidemiological findings across the nation; especially states with CDI incidence above the national baseline.

Insurance categories and HAI prevalence among different populations also draws attention for further research as existing literature presents with the cessation of Medicaid covering HAIs (Rhee et al., 2018) and the role that insurance plays in HAI exposure and prevention. Lastly, standardized practice of CDI management across all New Mexico facilities and nationally would benefit from extended research efforts. As mentioned in the literature review section, hospital service lines are determinants of hospital size, resources, and revenue—factors that correlate with characteristics such as length of stay. This would benefit from further analysis tests to indicate which service line had a stronger association with length of stay with, and independent of, a CDI diagnosis.

Implications for Professional Practice and Social Change

HAIs, especially CDI, can occur irrespective of socioeconomic and sociodemographic backgrounds. As evident in the findings from this study, individuals from larger income status present with the highest likelihood to be diagnosed with CDI. It remains vital to practice standard precautions in the prevention and management of CDI and other HAIs. This is especially important for controlling the transmission of HAIs across patients, healthcare workers, and the community. Continued development of public health and health initiatives and policies should be encouraged as it would strengthen practices such as antimicrobial stewardship, staff and patient education, reduction of length of stay, and hand hygiene compliance. Encouraging resource availability and appropriate allocation of resources across the healthcare facilities in the state of New Mexico can promote management of CDI, ensure equal distribution of tools and protocols for prevention of CDI, and reduce disparities across health communities. Standard precautions should be reviewed for uniformity across all healthcare facilities in New Mexico and align with the standard precautions accepted at the national level.

Conclusion

Observing the differences in sociodemographic access to health in facilities can also provide a scope of the management of CDI and other HAIs across populations. Developing specific programs and tools that serve different cultural backgrounds, needs, and health knowledge—for example, educating various age groups on HAIs—can serve as a proactive approach to combating barriers to health management. More importantly, it is valuable to identify the origins to health barriers and disparities such as hospital quality, staff and patient knowledge, health funding, and patient population composition and explore tools to promote improved and innovative health management. Standardization of health practice is key, however, being aware of societal limitations, obstacles, origins, ideas, attitudes, and accessibility to resource is the first step in promoting standardized universal health. In turn, such standardization will drive reduction in health and public health issues like CDI and other HAIs.

References

Abdullatif, V. N., & Noymer, A. (2016). Clostridium difficile infection: An emerging cause of death in the 21st century. *Biodemography and Social Biology*, *62*(2), 198–207. doi:10.1080/19485565.2016.1172957

Al-Tawfiq, J. A., & Tambyah, P. A. (2014). Healthcare associated infections (HAI) perspectives. *Journal of Infection and Public Health*, *7*(4), 339–344. doi:10.1016/j.jiph.2014.04.003

American Health Information Management Association [AHIMA]. (2018). AHIMA's long-term care health information practice and documentation guidelines: Practice guidelines for LTC health information and record systems. Retrieved from http://bok.ahima.org

Arpey, N. C., Gaglioti, A. H., & Rosenbaum, M. E. (2017). How socioeconomic status affects patient perceptions of health care: A qualitative study. *Journal of Primary Care & Community Health*, *8*(3), 169–175. doi:10.1177/2150131917697439

Austin, P. C., & Merlo, J. (2017). Intermediate and advanced topics in multilevel logistic regression analysis. *Statistics in Medicine*, *36*(20), 3257–3277. doi:10.1002/sim.7336

Balch, A., Wendelboe, A. M., Vesely, S. K., & Bratzler, D. W. (2017). Antibiotic prophylaxis for surgical site infections as a risk factor for infection with clostridium difficile. *PloS One*, *12*(6), e0179117. doi:10.1371/journal.pone.0179117

Barnett, M. L., Olenski, A. R., & Jena, A. B. (2017). Patient mortality during unannounced accreditation surveys at U.S. hospitals. *JAMA Internal Medicine*, *177*(5), 693–700. doi:10.1001/jamainternmed.2016.9685

Bekelis, K., Missios, S., Coy, S., & MacKenzie, T. A. (2018). Association of hospital teaching status with neurosurgical outcomes: An instrumental variable analysis. *World Neurosurgery*, *110*, 689–698. doi:10.1016/j.wneu.2017.11.071

Berzofsky, M., Smiley-McDonald, H., Moore, A., & Krebs, C. (2014). Measuring socioeconomic status (SES) in the NCVS: Background, options, and recommendations. Report. [Table 2-1. Victimization rates by type of crime and household income, 2010, p. 13.] Washington, DC: Bureau of Justice Statistics. Retrieved from https://www.bjs.gov/content/pub/pdf/Measuring_SES-Paper_authorship_corrected.pdf

Bloomfield, L. E., & Riley, T. V. (2016). Epidemiology and risk factors for community-associated *clostridium difficile* infection: A narrative review. *Infectious Diseases and Therapy*, *5*(3), 231–251. doi:10.1007/s40121-016-0117-y

Braveman, P. (2014). What are health disparities and health equity? We need to be clear. *Public Health Reports*, *129*(1_suppl2), 5–8. doi:10.1177/00333549141291s203

Brittin, J., Elijah-Barnwell, S., Nam, Y., Araz, O., Friedow, B., Jameton, A. ... Huang, T. T. K. (2015). Community-engaged public health research to inform hospital campus planning in a low socioeconomic status urban neighborhood. *HERD: Health Environments Research & Design Journal*, *8*(4), 12–24. doi:10.1177/1937586715575908

Bui, C., Zhu, E., Donnelley, M. A., Wilson, M. D., Morita, M., Cohen, S. H., & Brown, J.

(2016). Antimicrobial stewardship programs that target only high-cost, broad-spectrum antimicrobials miss opportunities to reduce clostridium difficile infections. *American Journal of Infection Control, 44*(12), 1684–1686. doi:10.1016/j.ajic.2016.06.025

Burke L. G., Frakt A. B., Khullar D., Orav E. J., & Jha A. K. (2017). Association between teaching status and mortality in U.S. Hospitals. *JAMA*, *317*(20), 2105–2113. doi:10.1001/jama.2017.5702

Calfee, D. P. (2012). Crisis in hospital-acquired, healthcare-associated infections. *Annual review of medicine, 63*, 359–371. doi:10.1146/annurev-med-081210-144458

Chitnis, A. S., Holzbauer, S. M., Belflower, R. M., Winston, L. G., Bamberg, W. M., Lyons, C., . . . Lessa F. C. (2013. Epidemiology of community-associated *clostridium difficile* infection, 2009 through 2011. *JAMA Internal Medicine, 173*(14), 1359–1367. doi:10.1001/jamainternmed.2013.7056

Dantes, R., Mu, Y., Hicks, L. A., Cohen, J., Bamberg, W., Beldavs, Z. G., … Lessa, F. C. (2015). Association between outpatient antibiotic prescribing practices and community-associated *clostridium difficile* infection. *Open Forum Infectious Diseases*, *2*(3), ofv113. doi:10.1093/ofid/ofv113

DePestel, D. D., & Aronoff, D. M. (2013). Epidemiology of *clostridium difficile* infection. *Journal of Pharmacy Practice*, *26*(5), 464–475. doi:10.1177/0897190013499521

Dubberke, E., Carling, P., Carrico, R., Donskey, C., Loo, V., McDonald, L. . . . Gerding, D. (2014). Strategies to prevent clostridium difficile infections in acute care hospitals: 2014 update. *Infection Control and Hospital Epidemiology*, *35*(6), 628–645. doi:10.1086/676023

Dudeck, M. A., Weiner, L. M., Malpiedi, P. J., Edwards, J. R., Peterson, K. D., & Sievert, D. M. (2013). Risk adjustment for healthcare facility-onset C. difficile and MRSA bacteremia laboratory-identified event reporting in NHSN. *Centers for Disease Control and Prevention*, *12*. Retrieved from https://www.cdc.gov/nhsn/PDFs/mrsa-cdi/RiskAdjustment-MRSA-CDI.pdf

Dudeck, M. A., Edwards, J. R., Allen-Bridson, K., Gross, C., Malpiedi, P. J., Peterson, K. D., ... Sievert, D. M. (2015). National Healthcare Safety Network report, data summary for 2013, device-associated module. *American Journal of Infection Control*, *43*(3), 206–221. doi:10.1016/j.ajic.2013.01.002

El-Saed, A., Balkhy, H. H., & Weber, D. J. (2013). Benchmarking local healthcare-associated infections: available benchmarks and interpretation challenges. *Journal of Infection and Public Health*, *6*(5), 323–330. doi:10.1016/j.jiph.2013.05.001

Eze, P., Balsells, E., Kyaw, M. H., & Nair, H. (2017). Risk factors for *clostridium difficile* infections: An overview of the evidence base and challenges in data synthesis. *Journal of Global Health*, *7*(1), 010417. doi:10.7189/jogh.07.010417

Farrell, L., Gilman, M., Teszner, E., Coffin, S. E., & Sammons, J. S. (2015). Present or absent on admission: Results of changes in National Healthcare Safety Network surveillance definitions. *American Journal of Infection Control*, *43*(10), 1128–1130. doi:10.1016/j.ajic.2015.05.023

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*, 1149–1160. doi:10.3758/brm.41.4.1149

Fine, M., & Viner-Brown, E. B. S. (2014). Rhode Island clostridium difficile infection trends and laboratory ID events ranking. *Rhode Island Medical Journal (2013)*, *97*(6), 60–63. Retrieved from http://www.rimed.org/publications.asp

Fischer, M., Kao, D., Mehta, S. R., Martin, T., Dimitry, J., Keshteli, A. H., ... Kelly, C. R. (2016). Predictors of early failure after fecal microbiota transplantation for the therapy of clostridium difficile infection: A multicenter study. *The American Journal of Gastroenterology*, *111*(7), 1024. doi:10.1038/ajg.2016.180

Ghose, C. (2013). Clostridium difficile infection in the 21st century. *Emerging Microbes & Infections*, *2*(9), e62. doi:10.1038/emi.2013.62

Gohil, S. K., Datta, R., Cao, C., Phelan, M. J., Nguyen, V., Rowther, A. A., & Huang, S. S. (2015). Impact of hospital population case-mix, including poverty, on hospital all-cause and infection-related 30-day readmission rates. *Clinical Infectious Diseases: An Official Publication of the Infectious Diseases Society of America*, *61*(8), 1235–1243. doi:10.1093/cid/civ539

Haas, L. R., Takahashi, P. Y., Shah, N. D., Stroebel, R. J., Bernard, M. E., Finnie, D. M., & Naessens, J. M. (2013). Risk-stratification methods for identifying patients for care coordination. *The American Journal of Managed Care*, *19*(9), 725-732. Retrieved from https://www.ajmc.com/journals/issue/2013/2013-1-vol19-n9/risk-stratification-methods-for-identifying-patients-for-care-coordination

Hadler, J. L., Danila, R., Cieslak, P. R., Meek, J. I., Schaffner, W., Smith, K., ... Lynfield, R. (2015). Emerging Infections Program—state health department perspective. *Emerging Infectious Diseases, 21*(9), 1510–1515. doi:10.3201/eid2109.150428.

Hasnain-Wynia, R., & Baker, D. W. (2006). Obtaining data on patient race, ethnicity, and primary language in health care organizations: Current challenges and proposed solutions. *Health Services Research*, *41*(4 Pt 1), 1501–1518. doi:10.1111/j.1475-6773.2006.00552.x

Henderson, V. C., Kimmelman, J., Fergusson, D., Grimshaw, J. M., & Hackam, D. G. (2013). Threats to validity in the design and conduct of preclinical efficacy studies: A systematic review of guidelines for in vivo animal experiments. *PLoS Medicine*, *10*(7), e1001489. doi:10.1371/journal.pmed.1001489

Herzig, C. T. A., Reagan, J., Pogorzelska-Maziarz, M., Srinath, D., & Stone, P. W. (2015). State-mandated reporting of health care-associated infections in the United States: Trends over time. *American Journal of Medical Quality: The Official Journal of the American College of Medical Quality*, *30*(5), 417–424. doi:10.1177/1062860614540200

Hidalgo, B., & Goodman, M. (2013). Multivariate or Multivariable Regression? *American Journal of Public Health*, *103*(1). Doi: 10.2105/AJPH.2012.300897.

Horton, H. A., Dezfoli, S., Berel, D., Hirsch, J., Ippoliti, A., McGovern, D., ... Fleshner, P. (2014). Antibiotics for treatment of clostridium difficile infection in hospitalized patients with inflammatory bowel disease. *Antimicrobial Agents and Chemotherapy*, *58*(9), 5054-5059. doi: 10.1128/AAC.02606-13

Jullian-Desayes, I., Landelle, C., Mallaret, M., Brun-Buisson, C., & Barbut, F. (2017). clostridium difficile contamination of health care workers' hands and its potential contribution to the spread of infection: Review of the literature. *American Journal of Infection Control, 45*(1), 51-58. doi:10.1016/j.ajic.2016.08.017

Kangovi, S., Barg, F. K., Carter, T., Long, J. A., Shannon, R., & Grande, D. (2013). Understanding why patients of low socioeconomic status prefer hospitals over ambulatory care. *Health Affairs*, *32*(7), 1196-1203. doi: 10.1377/hlthaff.2012.0825

Keezer, M.R. & Sanders, J.W. (2016). Comorbidity as an epidemiological construct. *Lancet Neurology*, *15*(1), pp. 32-32. doi: 10.1016/S1474-4422(15)00352-X

Kim, T. K. (2015). T test as a parametric statistic. *Korean Journal of Anesthesiology, 68*(6), 540–546. doi: 10.4097/kjae.2015.68.6.540

Leffler, D. A., & Lamont, J. T. (2015). Clostridium difficile infection. *New England Journal of Medicine, 372*(16), 1539-1548. doi: 10.1056/NEJMra1403772

Lessa, F. C., Mu, Y., Winston, L. G., Dumyati, G. K., Farley, M. M., Beldavs, Z. G., … Fridkin, S. K. (2014). Determinants of *clostridium difficile* infection incidence across diverse United States geographic locations. *Open Forum Infectious Diseases*, *1*(2), ofu048. doi: 10.1093/ofid/ofu048

Lessa, F. C., Mu, Y., Bamberg, W. M., Beldavs, Z. G., Dumyati, G. K., Dunn, J. R., ... & Wilson, L. E. (2015). Burden of clostridium difficile infection in the United States. *New England Journal of Medicine*, *372*(9), 825-834. doi: 10.1056/NEJMc1505190.

Magill, S. S., Edwards, J. R., Bamberg, W., Beldavs, Z. G., Dumyati, G., Kainer, M. A., ... & Ray, S. M. (2014). Multistate point-prevalence survey of health care–associated infections. *New England Journal of Medicine*, *370*(13), 1198-1208. doi: 10.1056/NEJMoa1306801

Magill, S. S., Wilson, L. E., Thompson, D. L., Ray, S. M., Nadle, J., Lynfield, R. … Emerging Infections Program hospital prevalence survey team. (2017). Reduction in the prevalence of healthcare-associated infections in U.S. acute care hospitals, 2015 vs 2011. *Open Forum Infectious Diseases, 4*(Suppl 1), S49. doi: 10.1093/ofid/ofx162.116

Mayr, S., Erdfelder, E., Buchner, A., & Faul, F. (2007). A short tutorial of GPower. *Tutorials in Quantitative Methods for Psychology, 3*(2), 51-59. doi: 10.20982/tqmp.03.2.p051

Meghani, S. H., Buck, H. G., Dickson, V. V., Hammer, M. J., Rabelo-Silva, E. R., Clark, R., & Naylor, M. D. (2013). The conceptualization and measurement of comorbidity: a review of the interprofessional discourse. *Nursing Research and Practice*, *2013.* doi: 10.1155/2013/192782

Miller, A. C. (2015). "clostridium difficile infection as a novel marker for hospital quality, efficiency and other factors associated with prolonged inpatient length of stay." PhD (Doctor of Philosophy) thesis, University of Iowa, 2015. Retrieved from http://ir.uiowa.edu/etd/1884.

Miller, A. C., Polgreen, L. A., Cavanaugh, J. E., & Polgreen, P. M. (2016). Hospital *clostridium difficile* infection rates and prediction of length of stay in patients without *C. difficile* Infection. *Infection Control and Hospital Epidemiology*, *37*(4), 404–410. doi: 10.1017/ice.2015.340

Napolitano, L. M., & Edmiston, C. E. (2017). Clostridium difficile disease: diagnosis, pathogenesis, and treatment update. *Surgery*, *162*(2), 325-348. doi: 10.1016/j.surg.2017.01.018

New Mexico Department of Workforce Solutions. (2015). *New Mexico annual social and economic indicators: Statistical abstract for data users*. Retrieved from https://www.dws.state.nm.us/Portals/0/DM/LMI/ASEI_2015.pdf

New Mexico Department of Workforce Solutions. (2016). *New Mexico annual social and economic indicators: Statistical abstract for data users*. Retrieved from https://www.dws.state.nm.us/Portals/0/2016_ASEI.pdf

New Mexico Department of Workforce Solutions. (2017). *New Mexico annual social and economic indicators: Statistical abstract for data users*. Retrieved from https://www.dws.state.nm.us/Portals/0/DM/LMI/ASEI_2017.pdf

Ozgur, C., Kleckner, M., & Li, Y. (2015). Selection of statistical software for solving big data problems: A guide for businesses, students, and universities. *SAGE Open*, *5*(2). doi:10.1177/2158244015584379

Pechal, A., Lin, K., Allen, S., & Reveles, K. (2016). National age group trends in clostridium difficile infection incidence and health outcomes in United States Community Hospitals. *BMC infectious diseases*, *16*(1), 682. doi:10.1186/s12879-016-2027-8

Rhee, C., Wang, R., Jentzsch, M. S., Hsu, H., Kawai, A. T., Jin, R., … Lee, G. M. (2018).

Impact of the 2012 Medicaid Health Care-Acquired Conditions Policy on Catheter-Associated Urinary Tract Infection and Vascular Catheter-Associated Infection Billing Rates. *Open Forum Infectious Diseases*, *5*(9), ofy204. doi:10.1093/ofid/ofy204

Safdar, N., Anderson, D., Braun, B., Carling, P., Cohen, S., Donskey, C. . . . On behalf of the Research Committee of the Society for Healthcare Epidemiology of America. (2014). The evolving landscape of healthcare-associated infections: Recent advances in prevention and a road map for research. *Infection Control and Hospital Epidemiology, 35*(5), 480-493. doi:10.1086/675821

Sandberg, K. C., Davis, M. M., Gebremariam, A., & Adler, J. (2015). Disproportionate rise in clostridium difficile-associated hospitalizations among US youth with inflammatory bowel disease, 1997-2011. *Journal of Pediatric Gastroenterology and Nutrition*, *60*(4), 486–492. doi:10.1097/MPG.0000000000000636

Shahian, D. M., Liu, X., Meyer, G. S., & Normand, S. L. T. (2014). Comparing teaching versus nonteaching hospitals: the association of patient characteristics with teaching intensity for three common medical conditions. *Academic Medicine*, *89*(1), 94-106. doi: 10.1097/ACM.0000000000000050

Shaner-McRae, H., McRae, G., Jas, V. (2007). Environmentally safe health care agencies: Nursing's responsibility, Nightingale's legacy. *The Online Journal of Issues in Nursing*, *12*(2), Manusript 1. doi: 10.3912/OJIN.Vol12No02Man01

Smetana J., Čečetková B., Chlíbek R. (2014). Prevalence study of nosocomial infections in university hospitals in the Czech Republic. *Epidemiology, Microbiology,* *Immunology*, *63*(4), 251-258. Retrieved from http://www.prolekare.cz/

Sommet, N. & Morselli, D., (2017). Keep Calm and Learn Multilevel Logistic Modeling: A Simplified Three-Step Procedure Using Stata, R, Mplus, and SPSS. *International Review of Social Psychology*. *30*(1), pp.203–218. doi:10.5334/irsp.90

Sperandei S. (2014). Understanding logistic regression analysis. *Biochemia Medica*, *24*(1), 12–18. doi:10.11613/BM.2014.003

Sperling, C., Noer, M. C., Christensen, I. J., Nielsen, M. L. S., Lidegaard, Ø., & Høgdall, C. (2013). Comorbidity is an independent prognostic factor for the survival of ovarian cancer: a Danish register-based cohort study from a clinical database. *Gynecologic Oncology*, *129*(1), 97-102. doi:10.1016/j.ygyno.2012.12.039

Tapper, E.B., Halbert, B., & Mellinger, J. (2016). Rates of and reasons for hospital readmissions in patients with cirrhosis: A multistate population-based cohort study. *Clinical Gastroenterology and Hepatology, 14*, 1181-1188. doi:10.1016/j.cgh.2016.04.009

Tung, V. S., Lopez, A., Orenstein, S. B., & Novitsky, Y. W. (2017). Necrotizing clostridium difficile enteritis complicating fulminant colitis. *Surgical Infections Case Reports*, *2*(1), 9-13. doi:10.1089/crsi.2016.0054

U.S. Census Bureau (2017). Small Area Health Insurance Estimates. Retrieved from http://www.census.gov/did/www/sahie/data/interactive/

Yu, K., Rho, J., Morcos, M., Nomura, J., Kaplan, D., Sakamoto, K., & ... Jones, J. (2014). Evaluation of dedicated infectious diseases pharmacists on antimicrobial stewardship teams. American journal of health-system pharmacy: AJHP: *Official Journal of the American Society of Health-System Pharmacists, 71*(12), 1019-1028. doi: 10.2146/ajhp130612

Zeigler, B. P., Redding, S. A., Leath, B. A., & Carter, E. L. (2014). Pathways community HUB: A model for coordination of community health care. *Population health management*, *17*(4), 199-201. doi:10.1089/pop.2014.0041.

Zhang, S., Palazuelos-Munoz, S., Balsells, E. M., Nair, H., Chit, A., & Kyaw, M. H. (2016). Cost of hospital management of *clostridium difficile* infection in United States—a meta-analysis and modelling study. *BMC Infectious Diseases*, *16*(1), 447. doi:10.1186/s12879-016-1786-6

Ziakas, P. D., Joyce, N., Zacharioudakis, I. M., Zervou, F. N., Besdine, R. W., Mor, V., & Mylonakis, E. (2016). Prevalence and impact of *clostridium difficile* infection in elderly residents of long-term care facilities, 2011: A nationwide study. *Medicine*, *95*(31), e4187. doi:10.1097/MD.0000000000004187

Zimlichman, E., Henderson, D., Tamir, O., Franz, C., Song, P., Yamin, C. K. ... & Bates, D. W. (2013). Health care–associated infections: a meta-analysis of costs and financial impact on the US health care system. *JAMA Internal Medicine*, *173*(22), 2039-2046. doi:10.1001/jamainternmed.2013.9763