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Association Between Physician Characteristics and Surgical Errors in U.S. Hospitals

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MPH, Kaplan University, 2014

BSc, Washington Adventist University, 2012

Doctoral Study Submitted in Partial Fulfillment of

the Requirements for the Degree of

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Abstract

The high incidence of medical and surgical errors in U.S. hospitals and clinics affects patients' safety. Not enough is known about the relationship between physician characteristics and medical error rates. The purpose of this quantitative correlational study was to examine the relationship between selected physician characteristics and surgical errors in U.S. hospitals. The ecological model was used to understand personal and systemic factors that might be related to the incidence of surgical errors. Archived data from the National Practitioner Data Bank database of physician surgical errors were analyzed using bivariate and multivariate logistic regression analyses. Independent variables included physicians' home state, state of license, field of license, age group, and graduation year group. The dependent variable was surgical medical errors. Physicians' field of license and state of license were significantly associated with surgical error. Findings contribute to the knowledge base regarding the relationship between physician characteristics and surgical medical errors, and findings may be used to improve patient safety and medical care.

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Dedication

I dedicate this project to late Chief, Sir. Reuben Amadi, my father, educator, advisor, motivator, and model who taught me the values of hard work and who raised all his children to be decently behaved and skilled professionals in diverse disciplines.

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With honor, humility, and pride, I would like to thank God for his guidance and courage through my academic journey. I wish to acknowledge and extend my warm gratefulness to my daughter, Sapphire Onuoha, my husband, and my family for giving me their time, understanding, and endurance to do the program. I am thankful to my mother, Lolo, Lady Dorothy Amadi, who taught me the skill of patience to reach a goal. Specifically, my sincere thanks go to my doctoral study chair and mentor, Dr. Richard Jimenez. I want to thank my other doctoral study committee members, Dr. Chester Jones and the University Research Reviewer Dr. Simone Salandy, for believing in my study and helping it to come to a realization. Dr. Jimenez provided rapid, significant feedback and revision suggestions that made the doctoral study process less stressful. Also, I want to thank the Walden University faculty, staff, and instructors for the support I received from them throughout my educational process. Many thanks to my peers who advised me in the various courses and helped me achieve my goal. Finally, I also thank my editors who worked with me and helped keep my confidence thriving.

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Section 1: Foundation of the Study and Literature Review

Health care in general is affected by the problem of medical errors. Medical errors are a significant problem for hospitalized patients in health care settings. The Institute of Medicine (as cited in Slonim, LaFleur, Ahmed, & Joseph, 2003) reported that medical errors are the major causes of morbidity and mortality in hospital inpatients and outpatients, estimated at 44,000 deaths per year in the United States and costing approximately $17 to $29 billion annually. "Medical errors are undoubtedly underreported in administrative databases" (Slonim et al., 2003, p. 621). This social issue requires attention to protect patients from undesired injury, disability, death, and financial stress. It is important for health care organizations and providers to prevent the occurrence of medical errors and improve patient safety.

The purpose of this study was to explore the association between physician characteristics and surgical errors in U.S. hospitals. Section 1 of the study includes a discussion of the foundation of the study and a literature review. I present the problem statement and purpose of the study, state the research question and hypotheses, and describe the theoretical foundation and nature of the study. In the literature review section, I summarize the peer-reviewed literature within the last 10 years on medical errors, reporting of errors, epidemiology of medical and surgical errors, and surveillance of the issue.

Earlier articles were also referenced in examining the issue. Also, I describe the concepts and define key terms used in the study. Further, the literature presented in Section 1 also addresses the problems of medical error, rates of medical and surgical errors within the United States and abroad, the effect of the problem on the population's health, knowledge about reporting errors, causes of errors, and error prevention strategies. In Section 1, I also discuss applicable conceptual theories, gaps in literature, actions that may assist in creating social change as a result of the study, and the need for the present study. Most of the articles I identified in the literature search were descriptive. The synthesized and analyzed information provided in the literature review serves as the basis to transition to Section 2 of the study.

Problem Statement

The current evidence regarding medical errors in the United States is overwhelming, and medical and surgical errors account for millions of injuries every year (Becher & Chassin, 2001). Robblee and Nicklin (2003) established that a large percentage of providers report having had personal experiences with medical errors that resulted in serious health consequences including death, long-term disability, and severe pain.

Bosma, Veen, and Roukema (2011) pointed out that the precise incidence of medical errors and near misses cannot be determined because some errors may be subject to more underreporting than other types and would require improved practical identification and recording to support improved quality of care. Bosma et al. concluded in their study that medical errors are common in surgery. A provider's nondisclosure of medical errors to the hospital administration out of fear of malpractice litigation is one of the causes of low medical error reporting (Rowe, 2004).

Substandard care caused by the noncomprehensive empirical assessment of medical malpractice errors results in a high level of injury to patients (Brennan et al., 1991). In addition, despite proportional investment and persuasive efforts, reporting systems fail to capture adverse events (Classen et al., 2011). Reporting of wrong-site surgery and retained items is uncertain, suggesting there is a need for improved communication of adverse events data (Hempel et al., 2015). Despite the knowledge regarding incompleteness or nonreporting of medical errors by hospital management, there are calls and recommendations for improving methods for appropriate error reporting by providers, government, and public health authorities to improve reporting, prevent recurrences of the problem, and promote patient safety. I did not find any studies on the associations between physician characteristics and surgical errors in my review of the literature.

Purpose of the Study

In this quantitative study, I examined the association between physician characteristic and surgical errors in U.S. hospitals. I examined the association between selected independent variables and the outcome of surgical errors. Independent variables included physicians' work state, home state, state of license, field of license, age group, and graduation year group. My dependent variable was the outcome of surgical errors for the total number of cases representing patients in the national data set (National Practitioner Data Bank [NPDB], 2015).

Research Question and Hypotheses

Research question: What is the association between physician characteristics and the occurrence of surgical errors?

Null hypothesis (Ho): There is no association between selected physician characteristics and the occurrence of surgical errors.

Alternative hypothesis (Ha): There is an association between selected physician characteristics and the occurrence of surgical errors.

Theoretical Foundation for the Study

My study goal was to examine the relationship between independent variables (physician characteristics) and dependent variable (surgical errors). Surgical errors as a dependent variable have been associated with many independent risk factors such as lack of standard definition of medical error, lack of effective surveillance, underreporting of errors, hospital culture or punitive environment, and systems problems including lack of teamwork and communication. I chose the ecological model (EM), also called socialecological model (SCM) to help me understand the data and frame my analysis. The ecological model is a commonly used model of health care studies that emphasizes the relationships among multiple factors or determinants affecting health and is focused on both population-level and individual-level determinants of health and interventions (Miller, 2013).

In addition, the EM "highlights the importance of the social and physical environments that strongly shape patterns of disease and injury as well as our responses to them over the entire life cycle" (Miller, 2013, p. 8). Health (surgical error) under this model may be determined by influences at multiple levels that include public policy, community, institution, interpersonal factors, and intrapersonal factors (American College Health Association, 2015). I employed the health care EM to understand the etiological factors behind surgical errors because it provides a comprehensive view of the complex connections between health, treatment, outcome, and health care structure.

Moreover, health care EM recognizes environmental factors and influences that interact with and affect individual behavior. These factors can be the physical setting, the human characteristics of the people and surrounding public, and the organizational and social environment (American College Health Association, 2015). Also, health care practitioners, educators, patient safety leaders, and researchers recognize the value of human factors in addressing patient safety (Miller, 2013).

The EM provides a basic structure for ascertaining reasons for public health problems as well as for planning interventions (Reinboth, 2013, para. 1). The base of the model recognizes that public health problems are not caused only by human error but by a combination of factors on different levels that include intrapersonal factors and environmental factors. Intrapersonal factors tend to determine individuals' knowledge about public health problems, their thoughts about planned solutions, and their recognized visible benefits and problems (Reinboth, 2013). The EM model is not only used to detect problems, but it is also used to identify significant people, groups, and resources that can help to bring about positive changes (Reinboth, 2013). In an ecological model, health status and behavior are the outcomes of interest. The intrapersonal factors of the model are an individual's characteristics such as knowledge, demography, attitudes, behavior, self-concept, skills, and developmental history, which includes gender, values, goals, expectations, age, coping skills, health literacy, and skills in accessing health care (American College Health Association, 2015). The EM of health behavior was relevant for my study because it emphasizes the environmental and policy context of underreporting of surgical errors while taking into consideration social and psychological influences (Glanz, Rimer, & Viswanath, 2008). The specific aspects of

EM that affect or relate to the physician characteristics (independent variables) that I used in the study are the intrapersonal factors that are centered on perceptions and risk factors (e.g., how individuals' history and biological factors influence how they behave and increase their probability of becoming a victim of committing medical errors). The EM helped to explain the outcome of error later in life as the communication of an individual's risk factors (World Health Organization [WHO], 2015). Another intrapersonal characteristic factor of EM, demography, was related to physicians' work state and home state. Additionally, skills (e.g., physician qualifications) were related to physicians' state of license, field of license, and reporting/charting medical errors, whereas developmental history was related to age group and graduation year group. The physicians' graduation year was also related to physicians' knowledge (American College Health Association, 2015; Carayon & Wood, 2009).

Patient safety is an outcome that results from ecological factors such as influences of intrapersonal characteristics, which interact with individuals and affect their behavior. Evidence shows that handovers, the transfer of information from one provider to another, is critically significant to patient safety. Handovers significantly helps the transfer of knowledge that helps individual team members understand the priorities for patient treatment and future plans of care (Rose, 2016, para1). Perioperative and Postoperative handovers are a critical phase of during a patient's surgical procedure, providers as a result of their multitasking nature during surgery have greater potential for medical errors and loss of information (Rose, 2016, para, 2). For that reason, "to improve patient safety, it is important to observe the specific physician characteristics processes involved and the intrapersonal factors such as knowledge and attitudes, of the involved individuals that add either positively or negatively to processes and outcomes" (Carayon & Wood, 2009, p. 9).

The physician characteristic of age was related to behaviors. The intrapersonal level involved an individual's personality traits as well as his or her beliefs and level of knowledge. The attributes of the individual can moreover be used in combination with the other levels to influence behavior change from an interventional health promotion approach. The individual characteristics of the intrapersonal factors, such as knowledge, demography, behavior, skills, and developmental history relating to individual behaviors, can be described to relate physician characteristics through the application of theories, mostly known as theories of health behaviors, to better understand their associations (National Cancer Institute [NCI], 2015). For this study, the health belief model (HBM) was the intrapersonal model that was suitable to help understand the relationship between the physician characteristics with the selected intrapersonal levels (Burke, 2013). The HBM was used to examine the perceptions and attitudes an individual may have toward negative outcomes of certain actions.

In this study, the HBM was based on individuals' understanding of taking a health-related action through their perceived susceptibility (risky behaviors) and perceived severity (perception and knowledge) (University of Twente, 2012). In this study, the health-related action of interest was the reporting of surgical errors. Underreporting of medical errors occurs in two ways: (a) human error due to carelessness, negligence, and other factors, in which solutions are achieved through disciplinary actions, blame, or lawsuits and (b) systemic factors, which are viewed as the end result and not the cause. Under the HBM constructs, the cue to action and selfefficacy solutions to errors are based on the belief that conditions can be changed through readiness and taking action (Glanz et al., 2008). It was important to focus on how and why the system failed (Medscape, 2015).

Kumar et al. (2012) argued that researchers rarely examine the importance of the different levels of the SCM to analyze health behavior decisions. Based on this, Kumar et al. sought to examine the use of SCM in studying influenza vaccine uptake during the 2009 HINI pandemic outbreak. The study focused on the intrapersonal factors of the model as determinants. The determinants were measured as attitudes toward the virus, including perceived risk, acceptance and safety of vaccines, and vaccination uptake. The findings revealed that the intrapersonal level of the SCM had the highest prediction rate (53%) of vaccine uptake of the five levels of SCM measured. Kumar et al. further explained that "attitude and beliefs are the typically measurable variables of the intrapersonal level of influence" (p. 2). The perceptions obtained from these human factors will create an impact on vaccine uptake. Moreover, these are actions based on behavior theories such as the HBM. Kumar et al. suggested that intrapersonal variables and specific attitudes may help determine vaccine acceptance and that knowledge about the problem may also be an important intrapersonal influence on behaviors.

Crosby, Salazar, and DiClemente (2011) supported this idea in their discussion of ecology approaches in the new public health and explained that the "basic premise of ecological thinking is that health behavior and their determinants are interrelated" (p. 232). Moreover, the basic function of the ecological approach is to use available means to contribute to long-term behavior change. Kumar et al. (2012) demonstrated that the ecological model has been used to characterize descriptive approaches and encourage population health. It has been used to measure and explain the effects of the causes and consequences of health problems. Kumar et al. (2012) further showed that the EM was developed as a result of lessons learned from system failures of health promotion programs. Failure, however, was understood as “a process that can be a catalyst for change” (p. 234).

Nature of the Study

I conducted a quantitative correlational study to measure the association between independent and dependent variables. My independent variables included selected physician characteristics: physicians’ work state, home state, state of license, field of license, age group, and graduation year group. My dependent variable was the outcome of surgical error in the total number of cases representing patients in the national data set (NPDB, 2015). I collected the data for the analysis from the National Practitioner Data Bank (NPDB) from the Health Resource and Service Administration of the U.S. Department of Health & Human Services (NPDB, 2015).

The NPDB is a federal information source established to improve health care quality, promote patient safety, and increase professional practice security. Data are collected for the database from health care organizations registered with the NPDB in accordance with federal regulations. The data are submitted online using the NPDB’s secure system or through external applications by authorized employees of the registered organizations, such as an administrator or risk manager. The NPDB has numerous sections relevant for researchers to obtain research statistics. The Public Use Data File section contains data on specific variables including Adverse Action Reports and Medical Malpractice Payment Reports reported by licensed health care practitioners, entities, providers, and others, as well as data from reports of Medicare and Medicaid exclusion actions (NPDB, 2015).

Data reports are maintained permanently in the NPDB database unless modified or removed by the reporting organization. The data are restructured quarterly and are for statistical analysis only (NPDB, 2015). I had access to this public use data set, and I confirmed that the database contained my variables of interest. Moreover, the reason for a secondary analysis of archived data (SAAD) for my study was that my project was a quantitative study. SAAD helped me to access a numeric estimate of my targeted population in a large data sample because the data contained combined information of my variables of interest from multiple sources (Green & Salkind, 2011).

SADD was convenient because I could obtain data very quickly, and it offered the capability to analyze and interpret results early. It was also cost-effective because I did not have to conduct primary research. In addition, I had an ethical consideration protection from any concern with my study affecting study participants because the data were de-identified. I described the data and population through descriptive analysis using the SPSS software. I also conducted inferential statistical analysis using SPSS to examine the association between the independent variables and the dependent variable through the application of bivariate analysis and multivariate logistic regression (Green & Salkind, 2011).

Literature Review

Literature Search Strategy

The key themes central to the literature review included U.S. and global rates of medical errors and surgical errors. Moreover, diverse search terms were used to find and collect full-text PDFs from a broad range of databases. The search terms included *rates of medical errors*, *patient safety*, *adverse events (ADEs)*, *medical error and surgical error reporting*, *physician malpractice and disclosure*, and *rates of surgical errors*. The primary databases used included Agency for Healthcare Research and Quality (AHRQ), WorldCat, PubMed, Springer, *Biomedical Central, Biomedical Journal, JAMA*, Ovid, ProQuest, Advisory Board Company, IOM, and Sage. The reason for the choice of these databases was to maximize search results given the abundance of related articles on the research problem. I also used the Google Scholar search engine. Web-based searches focused on Consumer Reports, Healthcare Affaires.Org, American Medical News (AMA), Hopkins Medicine.Org, Department of Health Policy & Management at the Harvard School of Public Health, International Society for Quality in Healthcare, Society of General Internal Medicine, National Quality Forum, American Surgical Association, and World Health Organization (NCBI-NIM-NIH).

The articles and journals I selected for the literature review were published from 2007 to the present and written in English. A chronological pattern was used to describe the literature and was organized by headings and subheadings. In the literature review, I first define medical errors, and then I describe the epidemiology of medical and surgical error rates in the U.S. and globally, the impact of medical errors on population health, causes of medical errors, gaps to date on the issue, and how this study will help close the gaps. Second, I include further evidence to support the study that includes research to date on the issue and the definition and types of medical errors to provide a thorough understanding of the nature of the problem. Finally, I present an overview of the literature related to the methodology of my study, and as evidence that the method can be applied to patient safety and used to identify surgical error occurrences. These factors are important for the identification of the constructs examined that contribute to the observed problem and literature gaps, which would function as a foundation for summarizing the research problem and purpose. Other evidence of patient safety intervention strategies is also presented.

Medical Errors Defined and Typology of Medical Errors

Public attention to medical errors in the United States began in part as a result of a 1994 death from breast cancer surgery due to medication error, reported by Lehman (as cited in National Academy of Sciences, 2015). The literature revealed that in a separate case, 15-year-old Lewis B. was also put at risk with undiagnosed complications after surgery that led to his death (National Academy of Sciences, 2015). In 1999, an Institute of Medicine (IOM) reported "an epidemic of medical errors in the USA" (p. 2). As the years went by, medical errors (also called "preventable medical mistakes") became "the third leading cause of death in the USA claiming 210,000 of people each year" (IOM, 1999, p. 2).

The National Academy of Sciences (2015) identified that the fear of discovery resulted in underreporting of medical errors and the inability to collect enough data for analyzing ADEs, which slowed the progress of patient safety efforts. In reaction to the increasing concern regarding the problem, the IOM (1999) directed its focus to the issue of medical errors and patient safety. To support this action, the Healthcare Research and Quality Act of 1999 mandated the Agency for Healthcare Research and Quality (ARHQ) to support research and build social partnerships that aim to identify the causes of preventable adverse errors and patient injury, as well as strategies for their reduction

(RadPhyscis, 2015). In 2000, the Patient Safety and Quality Improvement Act was established to collect data and report on medical errors in each state. Additionally, since 2000, to help trace the incidence of medical errors, a number of patient safety advisory groups have been formed, including the Illinois Adverse Health Care Events Reporting Advisory Council, Betsy Lehman Center for Patient Safety and Medical Error Reduction (Massachusetts), and Nevada Hospital Association Sentinel Events Registry Work Group, among others (RadPhyscis, 2015). RadPhyscis (2015) pointed out that "in 2002, the National Quality Foundation (NQF) issued a list of 27 serious ('never') reportable events for hospitals" and "the AHRQ established safety indicators (PDIs) in 2003 used as a measuring and monitoring tool for medical errors" (para.7.

Definitions. A review of the literature revealed that the major concern relating to medical error discussions and research is "the lack of a single definition of the term" (National Academy of Sciences, 2015, p. 9). La Pietra, Calligaris, Molendini, Quattrin, and Brusaferro (2005) reported that there are many definitions of medical errors in existence, but only a few produced by valued sources are worthy of consideration. Even though the definitions vary across the literature, a federal entity overseen by the AHRQ defines medical error as "the failure of not finalizing a planned action as envisioned using incorrect strategy to accomplish a purpose" (IOM, 1999; National Academy of Sciences, 2015, p. 10). Medical errors, moreover, are referred to as adverse events, sentinel events, and near misses:

1. Adverse events: Injuries caused by medical management rather than the causal condition of the patient (e.g., medical negligence, intentional misconduct, default of healthcare practitioner, and others).

2. Sentinel events: Unexpected events involving deaths or serious injuries (physical/psychological).
3. Near misses: Potential adverse events and errors that did not result in harm because of system intervention, as well as serious reportable event (SRE),which are events caused by errors in health care settings involving death or serious harm to a patient. In addition, SRE are devastating events and are preventable. Health care organizations are advancing to totally eliminate them. (Wilson Shepard Education Associates, 2015)

Typology of medical errors. Medical errors have been classified according to groups and categories in the literature. Wild Iris Medical Education, Inc. (2015) identified five subgroups of errors:

1. Surgical errors: Invasive hospital procedures that expose patients to risks involving death and serious physical and psychological injuries during treatment that include wrong-site surgery performed on the wrong body part, wrong procedure, and wrong patient.
2. Diagnostic errors: Diagnosis on the wrong patient or making diagnostic errors.
3. Medication errors: Preventable mistakes that can cause or lead to inappropriate medication use or patient harm while in control of the administrator.
4. Devices and equipment errors: The wrong connection of medical devices such as tubing, catheters, and syringes used to deliver medications or fluids to patients.

5. Systems failures errors: Systemic issues that cause medical errors such as falls (may cause fatal or nonsevere injuries such as hip fracture, head injuries, and increased risk of death); health care acquired infections (nosocomial infection or hospital acquired infection); and technology (equipment mis-connections). They include three main failures in planning (assessment, treatment, goals), communication among staff and physicians, and recognizing worsening patient situations.

Medical errors are categorized into two general categories: preventable adverse events (Table 1), which are errors that result in serious harm or death, and near misses, which are errors that result in no harm (National Academy of Sciences, 2015).

Table 1

The National Coordinating Council for Medication Error Reporting and Prevention (NCC MERP) Index for Categorizing Errors

Level	Description	Event
A	Circumstances or events occurred that had the capacity to cause error.	Harm does not reach patient
B	Error occurred but did not reach the patient.	
C	Error occurred that reached the patient but did not cause patient harm.	
D	Error occurred that reached the patient and required monitoring to preclude harm or confirm that it caused no harm.	

E	Error occurred that may have contributed to or resulted in temporary harm and required intervention.	Harm reaches patient
F	Error occurred that may have contributed to or resulted in harm and required an initial or prolonged hospital stay.	
G	Error occurred that contributed to or resulted in permanent patient harm.	
H	Error occurred that required intervention to sustain the patient's life.	
I	Error occurred that may have contributed to or resulted in patient death.	

Note. Reprinted from Levinson and General (2008).

Levinson and General (2008) grouped serious reportable events into six categories, including surgical events (Table 2). Surgical events include surgery performed on the wrong body part or wrong patient, wrong procedure performed on a patient, and unintended retained foreign objects in a patient's body after surgery and death. Among the different subgroups of errors, "surgical errors or surgical adverse events occur more frequent than all medical errors" (Wild Iris Medical Education, Inc., 2015, para. 18. In this study I focused on surgical errors.

Table 2

The National Quality Forum List of Serious Reportable Events

Surgical Events
A. Surgery Performed On The Wrong Body Part
B. Surgery performed on the wrong patient
C. Wrong surgical procedure performed on a patient
D. Unintended retention of foreign object in a patient after surgery or procedure

E. Intraoperative or immediately postoperative death
Product or Device Events
A. Patient death or serious disability associated with use of contaminated drugs, devices, or biologics provided by the health care facility
B. Patient death or serious disability associated with use or function of a device in patient care in which the device is used or functions other than as intended
C. Patient death or serious disability associated with intravascular air embolism that occurs while being cared for in a health care facility
Patient Protection Events
A. Infant discharged to the wrong person
B. Patient death or serious disability associated with patient elopement
C. Patient suicide, or attempted suicide resulting in serious disability, while being cared for in a health care facility
Care Management Events
A. Patient death or serious disability associated with a medication error
B. Patient death or serious disability associated with a hemolytic reaction because of administration of incompatible blood or blood products
C. Maternal death or serious disability associated with labor or delivery in a low-risk pregnancy while cared for in a health care facility
E. Death or serious disability associated with failure to identify and treat hyperbilirubinemia in neonates
F. Stage III or Stage IV pressure ulcers acquired after admission to a health care facility
G. Patient death or serious disability because of spinal manipulative therapy
H. Artificial insemination with the wrong donor sperm or wrong egg
Environmental Events
A. Patient death or serious disability associated with an electric shock while being cared for in a health care facility
B. Any incident in which a line designated for oxygen or other gas to be delivered to a patient contains the wrong gas or is contaminated by toxic substances
C. Patient death or serious disability associated with a burn incurred from any source while being cared for in a health care facility
D. Patient death or serious disability associated with a fall while being cared for in a health care facility
Criminal Events

A. Care provided by someone impersonating a health care provider
B. Abduction of a patient of any age
C. Sexual assault on a patient within or on the grounds of a health care facility
D. Death or significant injury resulting from a physical assault that occurs within or on the grounds of the facility

Note. Reprinted from Levinson and General (2008).

La Pietra et al. (2005) discussed the issues surrounding medical errors and clinical risk management. La Pietra et al.described medical error as “an unintended act that does not achieve its planned outcome” (p. 340). Medical errors in surgery are referred to as preventable adverse events; more specifically, the “adverse event caused by an error is a preventable adverse event” (p. 340). La Pietra et al. revealed that there are two factors involved that cause errors (Figure 1): active failures (human) and latent failures (structure or process). La Pietra et al. pointed out that active failure is hard to identify, whereas latent failure can be identified and corrected before an adverse error occurs. Errors are also classified according to the characteristics surrounding their occurrences: outcome, setting (inpatient or outpatient), type of procedure, and the likelihood of occurrence. La Pietra et al. suggested that the classifications be made known to physicians of specific specialties to promote safety improvements.

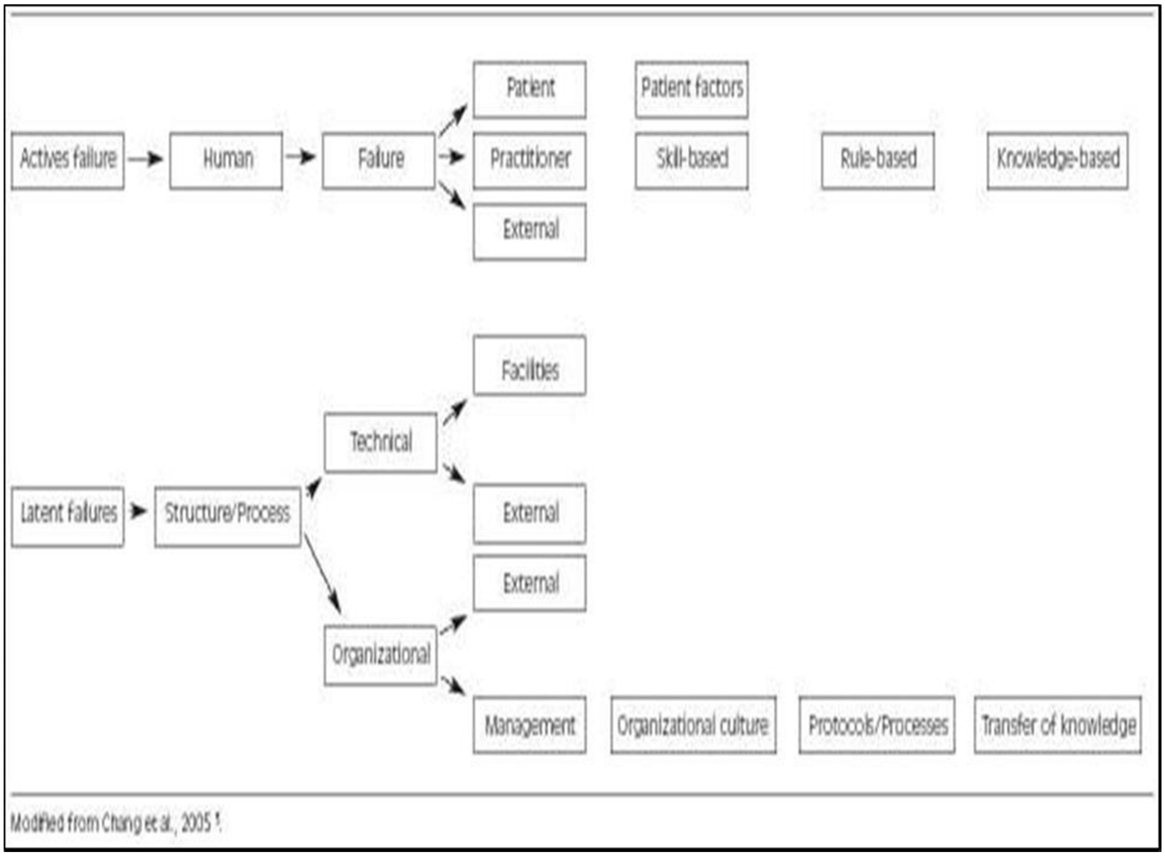

Figure 1. Classification of causes (Joint Commission on Accreditation of Healthcare Organization). Reprinted from La Pietra et al. (2005).

Epidemiology of Medical Errors Globally and in the United States

Globally, there are concerns about adverse events and researchers have focused on identifying them in hospitals. Harm from unsafe medical care due to medical error has resulted in significant degree of morbidity or mortality globally. Jha, Prasopa-Plaizier, Larizgoitia, and Bates (2010) stated that "tens of millions of people suffer injuries and millions are likely to die due to unsafe medical care," all related to serious adverse events of related surgical errors on hospitalized patients. The authors sought to understand causes and nature of unsafe medical care from a global perspective. Some evidence from the article identified the relationship between quality and safety as major causes of unsafe medical care. The identified causes were categorized into structure (the resources and organizational planning for care delivery), process (providers' actions for care delivery), and outcomes (the consequences of treatment by providers) (p. 42). With respect to the structural issue, human factor engineering (HFE) is an important factor described by the authors that may guide in patient safety improvement. HFE includes the organization arrangement referred to as informed approaches, communication, teamwork, accepted moral standards, information sharing, directed authorization, regulated accountability, and structured care (p. 44).

To complement Jha et al. (2010) study, Varallo, Guimarães, Abjaude, and Mastroianni (2014) examined the main cause of underreporting of medical errors by physicians and pharmacists, and found that ignorance, insecurity, and indifference were among the major causes that reduce the sensitivity for reporting ADEs, making it difficult to estimate the rate of occurrences. The authors listed seven attitudes related to ADEs underreporting, including fear of a lawsuit, guilt of responsibility, and ambition. Furthermore, the authors revealed that the rates of ADEs in other countries are largely unknown and underreported. They also found that applying the HFE technique and understanding the factors associated with the concern can encourage and assist in investigating medical errors and reducing their rates by maximizing human ability. The gaps in the literature include the need for reliable information on adverse events, systemic factors, and the effectiveness of existing prevention and harm reduction strategies. The literatures were credible and the authors identified how HFE strategies are important for behavior change intervention in reporting ADEs. The incorporation of continuing education for health professionals is seen as an effective measure toward attitude and behavior change to proper error reporting for patient safety improvement.

Developed countries that have similar practices to the U.S. hospital system also experience the same level of underreported surgical errors and system malfunction in their hospital system. Flotta, Rizza, Bianco, Pileggi, and Pavia (2012) sought to understand physicians' knowledge of patient safety, their attitudes, and management of medical errors in Italy through a national survey of selected physician characteristics. They found an inconsistency in physicians' concepts of patient safety practice. The researchers revealed that it is difficult to obtain a reliable estimate of errors and adverse outcomes that are frequent in the country, pointing out that "underreporting is a norm in the country" (p. 262). The authors argued that safety culture should be thoroughly assessed in hospitals as the initial step to identify problem areas for improvement because staff knowledge, attitude, and behavior are important to promote the environment required to secure hospital safety culture (p. 258). Some evidence from the article reveals the different rates of physicians' positive attitude about management, disclosure, and reporting of medical errors occurrences. Among physicians' characteristics, "poorly skilled professionals rate highest in the knowledge of causes of medical errors related to human factor" (p. 260).

In Japan, the nature and epidemiology of ADEs are similar to other countries but are more frequent per admission (Morimoto et al., 2011). According to Leflar (2009), legal policies and social institutions handling medical errors are less known, thereby "gaining traction over transparency and intensifying public concern over medical errors"

(p. 443). Leflar cited that the Japan health ministry in the intervention to address the problem undertook an assessment of physicians' transparency with relation to license and discipline to monitor the quality of care and identify iatrogenic events occurrences. Health officials hoped the process would regain public trust in patient safety practice by reliably assessing mistakes and improving patient safety. Higuchi, Higami, Takahama, Yamakawa, and Makimoto (2015) argued that it is important to monitor ADEs to improve the quality of care and suggested the system outcome-focused approach assessment as a reliable method to identify and report ADEs. The researchers encouraged health care professionals to communicate as a team to exchange information to improve patient safety.

In the U.S., an IOM report indicated that the issue of medical errors has drawn increasing attention since as early as the 1960s, revealing that patients were frequently injured by medical errors (AHRQ, 2015b). Medical error has long existed according to evidence in literature and has captured the public's attention by informing people of the extent of the problem. For example, "the IOM estimates that medical errors cause between 44,000 and 98,000 deaths annually in the United States, and rank as the eighth leading cause of death" (AHRQ, 2015b, para 1), killing more Americans than other health safety crises such as motor vehicle accidents, breast cancer, or AIDS (AHRQ, 2015b). Between 1990 and 2010, researchers estimated conservatively that 80,000 of surgical errors "never events" occurred in U.S. hospitals, and they believed their estimates was likely low (Makary, Mehtsun, Ibrahim, Diener-West, and Pronovost, 2012, para. 2). The literature reviewed revealed limitation in obtaining the actual rate of error in the hospitals and clinics, though it gave substantial evidence of estimated errors rates that may guide the improvement of patient safety practices in the healthcare system. In addition, the scope of the IOM report gave evidence that medical and surgical errors are considered a national emergency.

Several credible resources have reported the high frequency of medical errors in U.S. hospitals despite high levels of unreported or unrecorded events and addressed the issue from a patient safety management stance. James (2014) argued that the numbers of occurrences are immaterial and that what should matter the most is that lives are lost through medical mistakes. James cited that researchers have estimated 400,000 population deaths to be linked to medical error in U.S. hospitals on a yearly basis and that these preventable medical errors are the third leading cause of death in the nation (James, 2014; McCann, 2014). James's (2014) assumptions contradicted the effects of errors in his statement on medical errors numbers but established that the surge in medical error is a great patient safety concern.

The Leapfrog Group, a hospital rating organization, has released the current estimates of medical errors in the United States. The organization is among the most reliable, publicly reported hospital quality and safety capturing sources in the country, and its data source includes the University of Maryland Medical System provider and patient health care service and outcome data sets. Data from Leapfrog are found in their "Hospital Safety Score" webpage. It explains how hospitals keep its patients safe from errors such as injuries, accidents, and infections (University of Maryland Medical Center [UMMC], 2016). The estimated medical errors occurring in the United States are as follows (Leapfrog Group, 2016):

1. Approximately 440,000 people die yearly from hospital errors, injuries, accidents, and infections.
2. Annually, 1 out of every 25 patients develops an infection while in the hospital.
3. Medicare patients have a 1 in 4 chance of undergoing injury, harm or death when admitted to a hospital.
4. On a daily basis, 1000 people die from preventable hospital error. (Leapfrog Group, 2016)

Healthgrades has brought to light the variation in the nation's hospital quality outcomes in 2013, both locally and nationally, to inform consumers of hospital performance that can be a case of emergency. Healthgrades conducted an evaluation of nearly "40 million Medicare hospitalizations of 379 hospitals across Medicare patients in U.S. hospitals from 2009 through 2011 and they found 287,630 serious reportable adverse events" (Healthgrades, 2016, p.1) that are considered preventable adverse events. In Table 3 is shown the number of cases and events, per-1,000 rate, of 14 AHRQ-defined patient safety events (PSIs) (Healthgrades, 2016).

Table 3

Total number of PSIs, Cases, and Rates per 1,000 for 14 PSIs (2009–2011)

Patient Safety Event	Number of Cases	Rate per 1,000	Number of Events
Death in procedures where mortality is usually very low	3,239,650	1.00	3,229
Pressure sores or bed sores acquired in the hospital	13,526,349	0.65	8,812

Death following a serious complication after surgery	210,672	91.13	19,199
Foreign object left in body during a surgery or procedure	41,322,490	0.03	1082
Collapsed lung due to a procedure or surgery in or around the chest	39,501,863	0.38	15,037
Catheter-related bloodstream infections acquired at the hospital	27,550,553	0.25	6,885
Hip fracture following surgery	6,319,582	0.07	426
Excessive bruising or bleeding as a consequence of a procedure or surgery	10,769,962	1.61	17,370
Electrolyte and fluid imbalance following surgery	5,771,457	0.50	2,869
Respiratory failure following surgery	4,396,614	13.79	60,632
Deep blood clots in the lungs or legs following surgery	10,793,480	5.71	61,627
Bloodstream infection following surgery	1,384,370	12.59	17,433
Breakdown of abdominal incision site	1,327,317	2.64	3,507
Accidental cut, puncture, perforation or hemorrhage during medical care	41,322,490	1.68	69,522
Totals			287,630

Note. Reprinted from Healthgrades (2016).

Impact of Medical Errors on Patient Safety

Patient safety is relevant to the health of all individuals in the population. The damages resulting from medical errors are severe and in many cases lead to unnecessary deaths and disabilities in patients. Surgical patients are at a greater risk of errors due to the unresolved concerns of underreporting of medical error occurrences. According to the WHO (2009), Garrouste-Orgeas et al. (2012), and IOM (1999), there is a significant human and economic cost connected with adverse events. The human cost of additional care for pain and suffering leads to loss of independence and household productivity , as well as disability that may further create physical and psychological discomfort and have a substantial negative impact on individuals' quality of life (IOM, 1999). The errors also lead to patients' diminished satisfaction with and trust in treatments, which can result in weakened self-encouragement toward recovery. Patients on readmission due to ADEs or surgical error may exhibit delayed or total loss of confidence in their own healing process due to issues of harm from sustained errors that lead to various complication in their treatment outcomes (Garrouste-Orgeas et al., 2012).

Almader-Douglas (2013) stated that underreporting of surgical adverse events that occur in operating rooms and other medical errors in the hospital decrease the degree of health literacy needed to guide patients to make proper health decisions, leading to significant negative impact on people's health status by putting them at risk for hospitalization, preventable ADEs, higher use of emergency care, and death (p. 3).

Almader-Douglas (2013) pointed out that "patients are often faced with complex information and treatment decisions" because of their inability to analyze related risks and benefits, assess information for integrity and quality, and locate health information for adequate patient safety precautions. The author recognized health literacy as an example of a system issue that affects the delivery of health information and proper treatment direction. The researchers suggested that developing a safety culture in the hospital workforce and processes can help improve the reliability of care for patients and promote trust and security toward cure and recovery. The author recognized the need to identify these errors and efficiently report them through clear communication by providers and their patients as measures toward a substantive change in patient safety success.

Moreover, the excessive harm and death incidences from medical errors remain the key to uncover the actual numbers of medical errors to help reduce error occurrences. McCann (2014) expressed that cost related to medical errors is a huge financial burden to the U.S. at an estimate of $1 trillion annually. O'Reilly (2013) and Makary et al. (2012) reported that patients in the U.S. experience surgical errors at an estimate of "80 times each week" through wrong surgeries and surgical adverse events. They also pointed out the gap in tracking and reporting the errors. Thus, according to the authors, not enough has been done to address the problem, and there is the need for more focus on communication measures to collect reliable and comprehensive data information to enhance operational systems to reduce cognitive errors. The authors illustrated the importance of communication and information sharing as good approaches to promote patient safety in hospitals.

Null, Carolyn Dean, Feldman, and Rasio (2005) claimed that the present medical system repeatedly causes more harm than good. The authors revealed that "the number of unnecessary medical and surgical procedures performed annually is 7.5 million" (p. 21). The authors further estimated that these procedures produce a large number of iatrogenic medical events that are not-monitored, although there is a need to analyze them. According to the IOM (see Tables 4a and 4b), iatrogenic events are medical errors that include surgery, medication, and wrong procedures. They are rated as "the number one killer at 734,936 annual deaths" (p. 22). Researchers have established the need to assess individual and organizational factors that contribute to issues of medical errors in order to have a better understanding of its prevalence. Leapfrog (2016) pointed out that physicians and nurses are unequipped to deal with human error due to the culture of their training and practice, and Null et al. (2010) described errors as a "failure of character."

Table 4a

Estimated Annual Mortality and Economic Cost of Medical Intervention

Condition	Deaths	Cost
Adverse Drug Reactions	106,000	$12 billion
Medical error	98,000	$2 billion
Bedsores	115,000	$55 billion
Infection	88,000	$5 billion
Malnutrition	108,800	-----------
Outpatients	199,000	$77 billion
Unnecessary Procedures	37,136	$122 billion
Surgery-Related	32,000	$9 billion
Total	783,936	$282 billion

Note. Reprinted from Null et al. (2010).

Table 4b

Estimated 10-Year Unnecessary Medical Events

Unnecessary Events	10-year Number	Iatrogenic Events
Hospitalization	8.9 million	1.78 million
Procedures	7.5 million	1.30 million
Total	16.4 million	3.08 million

Note. Reprinted from Null et al. (2010).

Medical Error Surveillance and Reporting Systems

In a hospital care system, a reporting system serves two important purposes: provide information that would lead to an improved patient safety practice, and implement accountability measures for providers. Henriksen et al. (2005b) and National Academy of Sciences (2015) revealed that medical facilities have for a long time had a number of reporting systems available to monitor errors, including:

1. Mandatory reporting to external body: used by states that require an accountable reporting of adverse events from healthcare institutions, e.g., the Joint Commission on Accreditation of Healthcare Organization (JCAHO).
2. Voluntary, confidential reporting to external body: used for collecting and identifying causal factors of adverse events occurring in hospitals from frontline practitioners by telephone, internet, or mail for quality improvement, e.g., medication errors reporting system (MER) program and MedMARx program(internet-based medical error reporting system).
3. Mandatory internal reporting with audit: used to archive data in a standardized format and made available during hospital inspections, e.g., OSHA approach (create incidence rates of worksite complaint and injury that are tracked over a period). (Henriksen et al., 2005b)

Henriksen et al. stated that reports can be obtained from organizations with the advantage of eliciting organizations' commitment to make required changes. Reports also can be obtained from individuals, which provide the opportunity to receive input from practitioners (p. 6). The systems comprise charting incidents reports with an observable error, and the strategy is to identify trends or improvement recommendations. According to the National Academy of Sciences (2015), discussion of error-reporting system and mandatory and voluntary reporting are the two basic methods of reporting errors in the healthcare system. Mandatory approaches primarily hold providers accountable of detected serious injuries and errors, whereas the voluntary approach is focused on safety improvement and mostly on errors that do not result in harm or very minimal harm (p. 2). The authors pointed out that the significance of a reporting system is an advantage of commitment to make changes, and the opportunity to gain practitioners input on patient safety issues (p. 6). There is observed underreporting of errors regardless of the type of reporting system, and is most attributed to the factor of confidentiality (p. 17). In addition, the media exposure of the severity of medical errors is clear evidence of the inadequacy of system error monitoring (Henriksen et al., 2005a, p. 308).

Cohen (2000) discussed ADEs and error reporting in healthcare, and he cited the IOM report that indicated that both voluntary and mandatory error reporting systems are presently operating nationally at variable levels of success (p. 1). Cohen suggested that mandatory systems are necessary because providers and practitioners should be held accountable for their actions and patient safety. The aim is to encourage professional bodies to recognize patient safety in practice guidelines and to urge educational bodies to outline standards of practice because "healthcare providers have moral and ethical obligations to disclose and report errors honestly and promptly" (p. 6). The authors recommended an established reporting system that would provide for the national collection of standard information and the disclosure of serious medical errors.

Henriksen et al. (2005a) sought to determine the impact of a patient safety program on patterns of medical error reporting by implementing a patient safety program called the Medical Team Management (MTM). The MTM program focuses on communication, teamwork, and reporting errors. The study result reported an increased, significant number of errors reports, although there was an improvement in team management. The major focus of the program is on attitude, leadership, team training, and skill enhancement. Additionally, among the program's seven success elements, the ones most related to error reporting include medical team communication, situational awareness, daily operating strategy, and policies and regulations. Among all, communication was described as the leading factor in reporting medical mistakes, as it empowered team members to report (p. 313). Henriksen et al. (2005a) concluded that many approaches to patient safety have focused on improved training. According to Van Den Bos et al. (2011), medical error is a safety issue and quantifying the level of the problem is a fundamental step to addressing the problem. Van Den Bos et al. (2011) examined highquality healthcare cost as a measure to analyze the problem in order to identify and reduce the large numbers of medical and surgical errors. The authors argued that medical errors occur as a result of improper management. Van Den Bos et al. (2011) and Makary et al. (2012) cited many techniques that used actuarial approaches, such as medical claim data, as a means to identify these errors by measuring the frequency and cost of health care services attributed to medical and surgical errors, and found that these errors occurred frequently. The authors also provided evidence of an "estimated annual cost $37.6 billion for adverse events and $17 billion for medical postoperative complications regarding the issue" (Van Den Bos et al., 2011, p. 597). According to the authors, poor information remained the reason for the occurrence of errors, and they recommended team communication for proper error accounting. Nonetheless, there is considerable evidence that the tracking technique the authors used for error trends supported identifying and reporting errors. It is very unethical that in the healthcare service environment, acclaimed professionals with expert skills have created an image of patient harm and insecurity due to surgical errors occurring in the hospital outpatients and during surgical operations.

McCrory, LaGrange, and Hallbeck (2014) highlighted Leapfrog's statement arguing that to mitigate, prevent, identify errors and protect patients, multiple approaches can be used to improve the problem such as acknowledging and classifying clinical human and ergonomics factors that contribute to medical and surgical errors . The authors established that "there was no ubiquitous error check function in the OR; and that current research between clinicians and engineers' demonstrates the value of the error mitigation and practice." Also, the authors noted that it was important to "mitigate, study and identify errors or near misses in order to create a more resilient surgical system" (McCrory, et al., 2014).

Causes of Medical Errors

In my literature review, I identified five causes of medical error. Causes play a key role in understanding the nature of error that occurs in patient care and how they occur. It is important to understand what creates error and why errors occur. In this section, the observed causes of medical errors that I have described are lack of standard definition of medical error, lack of effective surveillance, underreporting of errors, hospital culture or punitive environment, and systems problems such as teamwork and communication.

Ghaleb et al. (2006) conducted a systematic study review to examine the incidences of medication errors in children and to identify common errors by applying three methods: spontaneous reporting, medication order or chart review, and observation. The authors found that there were inconsistencies in reported errors caused by different definitions of medical errors and reporting methods. Ghaleb et al. identified that it is important to provide a standard definition of errors because it would support the improvement of research reporting in that particular area (p. 1774). Weingart, Wilson, Gibberd, and Harrison (2000) reviewed the epidemiology of medical error with a primary focus on the risk factors for increased injury from errors. The authors discovered that inconsistent definitions of error, types of error, and faulty methods, including collaborative work on error measurement, may undermine the ability to report errors and are the causes of underreporting of error occurrences in hospitals. Weingart et al. (2000) pointed out that the precise prevalence and magnitude of errors cannot result from these factors and suggested the agreement in methods and definitions as a system for monitoring and reporting error that could provide a background for detailed studies of subpopulations (p. 776).

Seiden and Barach (2006) observed the wrong-side/wrong-site, wrong-procedure, and wrong-patient adverse events (WSPEs). The authors confirmed that patient case procedures are not coded discretely, making it difficult to clearly determine error frequencies. They also revealed that providers feel unsafe to report errors out of fear of litigation (Seiden & Barach, 2006, p.19). WSPEs occur more frequently than is reported; however, the authors suggested that the development of strong patient identification systems such as barcoding can improve human factors associated with improved error reporting (p. 20). Chung and Kotsis (2012) sought to introduce root cause analysis as a tool for identifying the causes of surgical complications. The authors found that voluntary reporting was not anonymous, and that possibly may have caused underreporting of errors because of fear of embarrassment or blame (p. 5). Chung and Kotsis (2012) suggested improved communication between providers, reporting systems, safety checklists, among other measure, to promote error reporting for patient safety.

Keers, Williams, Cooke, and Ashcroft (2013) used a systematic review of synthesized quantitative and qualitative data methods to observe the causes of medical errors in hospitals. The authors explained that the "misidentification or misinterpretation of medication or patients for treatment seems to occur frequently but the origin are not properly described" (p. 1063). The authors concluded that there is a lack of consistency in accounting for the causation of medication error (MEs) and suggested a strong theoretical observation to study the nature and complexity of MEs.

White, Pichert, Bledsoe, Irwin, and Entman (2005) investigated the medical claims with specific focus on the causal factor involved in obstetrics and gynecology patients who experienced adverse events. The authors identified documentation issues, such as unrecorded data, as a contributor to adverse events. They explained that underreporting of adverse events by risk managers is linked to missed patients outcomes. Jagsi et al. (2005) examined medical residents' reports on adverse events and their causes, and identified inadequate documentation again as a contributor for failure in perceiving and identifying adverse events. White et al. (2005) suggested that descriptive manager's tools such as analysis diagrams and coding system can be helpful in identifying errors for reduction (White et al., 2005. p. 1037). Hogan et al. (2012), in an effort to address the uncertain estimates of preventable adverse events associated with death or reduced life expectancy, applied a retrospective case record review study to examine preventable deaths that occurred in acute care hospitals in England. The cases were evaluated by cause and effect to identify the preventable errors. The authors used a Likert scale to produce a consistent and appropriate definition of the preventable errors for correct accounting purposes. The authors found that preventable deaths were more common in surgical units and were attributed to poor clinical monitoring, diagnostic error, and inadequate care management.

Farnan et al. (2012) carried out a review of the effect of clinical supervision on patient and residency education outcomes. Using a secondary analysis of archived data methodology, the authors reviewed articles from a variety of specialties, including emergency medicine, surgery, internal medicine, psychiatry, and anesthesia. The authors identified "inadequate supervision as a most common cause of medical errors during a patient admission" (p. 428).

Lawton, Carruthers, Gardner, Wright, and McEachan (2012b) sought to identify the latent failures underpinning medication administration errors. The authors identified latent failures to include "human resources, team communication, ward climate, policies & procedures, supervision & leadership, training and work environment" as causes of errors (see Table 5). Moreover, they emphasized that latent failures "manifest in working conditions to promote errors" (p. 1). Lawton et al. (2012) concluded that the development of a theory about latent failures in hospitals will aid in building a model to improve organizational-level patient safety interventions that would help in adequate reporting of errors and support the reduction of reduction of adverse events due to errors.

Table 5

Themes Representing Latent Failures in the Context of Medication Errors: Definitions, Secondary Themes

Theme	Secondary Themes	Definitions

Ward climate	Described below	The overall atmosphere of a hospital ward determined by predominantly unspoken, multidisciplinary shared assumptions, rules, and norms of "the way it is," which have evolved over time and forced individuals and teams to adapt to this environment
Human resources	Staffing levels Skill mix Temporary/contingent workers	Aspects of the provision of health care personnel, including the number of available permanent qualified staff, their respective skill-base, and the employment of contingent workers
Local working environment	Patient Ward design Personal issues Fatigue Ward noise levels Equipment design and availability Pharmacy and dispensing issues	Aspects of the individual or the immediate working environment such as work patterns and physical working conditions which hinder the provision of safe patient care and encourage the performance of unsafe acts
Team communication	Written Verbal Team size Multicultural issues	Aspects of an intra- or inter-departmental team or communication channels that prohibit effective communication between individuals or departments
Written policies and procedures	Policy knowledge Policy development	Aspects of the development and dissemination process of explicit written policies, guidelines, and procedures that impact upon the knowledge of and subsequent utilization by nursing staff
Supervision and leadership	Task delegation Leadership style	Aspects of immediate line management that impact upon the ability of subordinates to provide or be motivated to provide timely, coordinated, and safe patient care
Training	Induction and preceptorship (initial ward-based training) Ongoing training	The availability, appropriateness, and process of delivery of training to newly qualified and existing nursing staff

Note. Adapted from Lawton et al. (2012).

Through diverse methodologies, numerous researchers have conducted studies to learn about the causes of underreporting medical errors that cause adverse events in hospitals and clinics, such as case report and passive surveillance (Stratton, Howe, & Johnston, Jr., 1994). Flores, Abreu, Barone, Bachur, and Lin (2012) sought to understand medical interpretation among professional hospital interpreters that may be associated with error number, types of errors, and their potential clinical consequences. The authors conducted a correctional error analysis of audiotaped emergency department visits. They found that among professional interpreters, the hours of training rather than years of training are associated with error numbers, types of errors, and consequences. The authors found that "interpretation errors are common in emergency department, and emphasized that they have been documented to compromise patient safety or be associated with ADEs and serious injuries" (p. 551). The research demonstrated that limited proficiency in English could lead to misunderstanding in communication, patient satisfaction, and outcome, which may affect accurate reporting of errors.

The purpose of the systemic review by Lawton et al. (2012a) was to create an evidence-based framework of factors contributing to patient safety incidents in hospital settings. The study result identified active failure-errors, mistakes, and violation from act or behavior of the health professional as the major contributor to error incidents. Other factors, such as lack of communication and equipment failures, were most frequently reported together as the cause of medical errors. The authors of the study pointed out that poor evidence and lack of reliably adopted framework for analyzing risk and safety in healthcare can hamper the accurate reporting of error and the opportunity to learn from them. The authors suggested that a well-developed empirical framework of error contributing factors can help to improve the identification and prevention of preventable events that cause patient harm or injuries if applied in hospital settings (p.10). James

(2013) used an evidence-based approach called the Global Trigger Tool to estimate patient harm associated with hospital care. The author applied a four-fold method to identify and count patient adverse events: identify types; characterize preventable errors; examine prevalence and severity in records; and compare studies from the literature. James highlighted that researchers on preventable harm must make it essential to be assured of their finding capabilities. The study finding revealed that the application gave a more comprehensive and accurate evidence of serious medical error estimates (p. 124). The author concluded that teamwork that involves patients and providers to identify errors, as well as transparent accountability of these errors, is necessary to reduce error and improve patient safety in health care settings.

Preventing Medical Errors

I identified five main strategies for preventing medical errors: correctly defining medical errors, developing and implementing effective surveillance systems, properly and consistently reporting errors, addressing hospital culture or punitive environment, and using a systems approach to address medical errors with a focus on building teamwork and communication among practitioners.

According to Andrews et al. (1997) and Clarke, Johnston, and Finley (2007), data on the frequency of ADEs occurrences from medical records are represented falsely and underreported. However, significant research efforts have been undertaken by many investigators to uncover methods to report consistent occurring errors. The authors identified that many health care facilities have developed electronic reporting systems and identification of ADEs to improve patient safety.

Weingart et al. (2000) contended that the media often reports stories of terrible injuries that occur at the hands of physicians, highlighting the problem of medical errors but providing little insight into their origins. The authors explained that there is limited epidemiological information on errors and that “universal underreporting undermines the ability to measure error accurately” (p. 776). The authors explained that strong casefinding surveillance may help to identify errors and injuries not reported in patients charts. The authors further highlighted that using both chart review and self-reports from clinicians are good strategies for identifying ADEs. The authors explained that even though observational studies are expensive, they have identified higher rates of errors and injury occurrences during hospital care processes (p. 771). There is a need to use consistent definitions and methods and collaborative work on measuring errors. This approach could support researchers to monitor correctly and report errors in order to study delayed subpopulations and support patient safety intervention by healthcare organizations (p. 776). Henriksen et al. (2005) examined the feasibility of using hospitaldischarged data as a means for accurate reporting of errors. The authors cited IOM’s statements on the “need for better data on adverse event occurrences, and better approaches to monitoring patient safety.” According to AHRQ (2015a), other factors that cause medical errors include communication failures, human factors, technical failures, poor policies and procedures, and knowledge level (p. 5). La Pietra et al. (2005) found that the specific and general effects of medical errors are the preventable morbidity and mortality, poor patient satisfaction, fear and distrust in patient safety, and cost of prevention levied on the provider, practitioner, patient, and the population. The authors recommended proper monitoring and system changes to obtain medical error reporting information to improve patient safety, and "encourage the adoption of a systemic approach to patient safety be healthcare teams to share the responsibility to safety" (p. 345).

Leape et al. (1998) found that in 1995 a series of highly exposed medical error incidences linked to serious patients' adverse events triggered public and professional interest in patient safety (p. 1444). In an effort to address the problem, diverse initiatives have been implemented at all government levels to prevent further patient injuries from errors. Among them, the Veterans Health Administration (VHA) patient incident reporting system was reconstructed and linked to a centralized registry and reporting system that was aimed at reporting both sentinel and near misses as a requirement to conduct root cause analysis of the incidents (Leape et al., 1998, p. 1446). The VHA system has aimed to ensure consistent and high quality health care delivery among all Veterans Affairs hospitals and care delivery. Moreover, the VHA system has the advantage to disseminate knowledge about medical errors and measures for patient safety improvement. The VHA centralized system and the integrated service approach have successfully increased the reporting of medical errors and ADEs since its initiation in 1997 (p. 1446). The prevention, detection, and correction of an error in patient safety are the major goals of the VHA system. The authors suggested the design of a culture of recognition, proper accounting, and reporting of errors by health care practitioners and other caregivers who identify adverse events in order to support the promotion of patient safety in healthcare.

Zhan and Miller (2003) examined the use of administrative data tools-based patient safety research. They argued that "the first and most critical obstacle in the patient safety campaign is the lack of a system that can reliably identify and report medical errors" (para, 1). Moreover, an effective reporting system is the basis on which to study the degree of the problem, to identify its risks and associated factors, to find possible solutions, and to measure the effectiveness of the intervention. The authors revealed that a reliable reporting system would "involve triangulation between current administrative data, chart review, and self-reports to maximize the amount of information to medical errors." The study concluded that administrative data are a good source and are highly recognized in patient safety research.

Thomas and Petersen (2003) described that measurement is precise and accurate information that can be analyzed statistically. It can help capture error event and facilitate proper reports. The authors explained that "promoting patient culture will encourage and support the reporting of errors at all condition that threatens patients' safety," and suggested that "medical staff should review and report errors in discharge report." In addition, Brady et al. (2009) explained that a cultural modification in the work environment would be required to support error disclosure with all personnel in order to produce accurate and accessible data that can be used to influence change in medical practice and promote patient safety.

Further, Zineldin, Zineldin, and Vasicheva (2014) pointed out that "by not disclosing errors the physician fails the patient." Lawton and Parker (2002) observed the willingness of health care professionals to report the mistakes of others. They explained that maintaining and improving the quality of care is based on knowledge from mistakes. The authors found that among health care professionals, physicians, in particular, are unwilling to report adverse events. The article further revealed that human factor is the major contributory factor to errors. To promote improvement, the differences between active and latent failures were established, and an approach to error management was adopted within the work system that can help reduce latent and active failures in healthcare (p. 16). The authors suggested that failure of behaviors or practices in error management, e.g., learning from their adverse events, near misses, and complaints, should be addressed to achieve organizational learning improvement. The authors described error management as a formal report of conditions where compliance with a protocol will lead to good patient outcome and increase improvement on existing protocol (p. 17). The strategy will promote better outcomes reporting by giving the organizations the opportunity to learn from experience that would help measure and minimize adverse incidents of latent failures, including causes of latent failure behavior or practice within their work system. In conclusion, the authors proposed the development of other organizational learning processes that would identify failures before an adverse event occurs.

Kumar and Steinebach (2008) stated that medical errors have contributed to the high cost of health care, and that the main causes of deaths and injuries of many patients annually "have continued to increase steadily since the 1980s" (p. 444). The authors examined what has been done about the problem in the last two decades and presented a close-loop, mistake-proof operation system for surgery processes that may reduce or eliminate preventable medical errors. According to the authors, the system is a combination of service framework of a Six Sigma DMAIC cycle that includes define, measure, analyze, improve, control, and cause-and-effect diagrams and poka-yokes operation process:

1. Define – set patients priorities for surgery: treatment performed correctly, no pain, on time, no injuries or medical errors encountered.
2. Measure – data are collected to evaluate the practice performance level.
3. Analyze – causes of failures are detected that may create medical error and result in adverse event.
4. Improve – remove the causes of failures identified.
5. Control – document patient flow process during surgery and understand how to maintain realized improvement from the applied processes. Also, it is important to encourage the use of process protocols by practitioners.
6. Cause-and-effect diagrams – used to communicate cause and effect that may lead to unwanted failures manner.
7. Poka-yokes – (avoid mistakes) operation process: designed method that easily captures error and makes corrections. (Kumar & Steinebach, 2008, p. 453)

Six Sigma is an approach and system used by organizations to exclude failures in their practices for performance improvement in employee morale that would lead to quality practice (p. 444). However, a significant unanswered question surrounding the rate of prolonged surgical errors in the hospitals and the potential for hospital surgical error experience has risen for the medical and scientific communities. The available evidence suggests that "surgical errors adverse events are at a rate more than or almost equal to those related to motor accidents" (p. 449). The authors asserted that the process will significantly reduce errors. They pointed out that the poka-yoke level operation process can help hospital processes attain patient goals. Kumar and Steinebach (2008) suggested that health care providers should invest in improving quality service education for doctors and staff. Zineldin et al. (2014) argued that the potential for measuring medical error and ADEs rates is difficult given more inadequate reporting than other health care process and outcomes because they need to be understood in the framework of their occurring system (p. 64).

Zeeshan, Dembe, Seiber, and Lu (2014) investigated the incidence of ADEs that occurred during surgical hospitalization in U.S. health care system by conducting a systemic assessment of targeted patient health records using the electronic reporting system (ERS) of ICD-9-CM surgical procedural codes (p. 2). The authors explained that ERS have been developed and used by several health care systems to identify and report AEs for the purpose of taking a proper quality assurance measures. ERS is a record based tool that contains data of patients' health information that are de-identified and coded to protect patient identities. For this study, data that did not contain patients' key surgical procedures were excluded, and the population characteristics studied included patient demographics and types of surgical procedures performed and coded according to care categories, e.g., case management, invasive procedure, and equipment or devices used for incident report. The study was designed to determine the correlation between surgeries performed and reported AEs rate. The results showed low report rates of AEs and identified that a typical surgical AEs frequently involved inadequate case management, such as poor documentation. The authors argued that a systemic assessment can be useful for surgeons and hospital personnel to detect the variations of AEs rates to help develop directed intervention for improvement (p. 1). The authors illustrated the importance of using information and communication approach to cause behavior change for proper and accountable reporting of surgical errors in health care to improve patient safety. Mazzocco et al. (2009) wanted to determine if good teamwork had better outcomes than poor teamwork in patient care. The study was conducted in the surgical rooms of ambulatory and medical centers. The authors found that good team work included information sharing and briefing during all surgical phases. These strategies decreased the probability of serious adverse surgical complications. The authors stated that there is a need for health care organizations to "promote effective team functioning to create a safe system of health care delivery." Centered on this evidence, the authors concluded that "the study supports arguments for human factors training for surgical teams."

Literature Related to the Proposed Methodology

Secondary analysis of archived data as a viable research method. For this study, I used a secondary analysis of archived data. Information technology advances have allowed for the collection of large amounts of data for quick access by researchers. As early as 1963, nearly 50 years ago, the concept of archived data analysis was introduced by Barney Glaser of re-analyzing data that were originally collected for other purposes, which can lead to new fundamental social knowledge (Johnston, 2014; Andrews, Higgins, Andrews, & Lalor, 2012; Long-Sutehall, Sque, & Addington-Hall, 2010). Moreover, the use of existing data has become very prevalent and frequently used as secondary analysis in research. According to Johnston (2012), secondary analysis of archived data is an important method in a research study. The author's definition of secondary analysis of archived data is "further analysis of an existing data set which presents interpretation," or the analysis of data that was collected by a separate individual for another primary goal. The literature revealed that secondary analysis of archived data is a systemic method and empirical practice that applies similar research procedure and evaluation steps as primary data.

Long-Sutehall et al. (2010) maintained that secondary analysis of archived data is a viable method used in social and health research. Most research examines what is unknown from the known through reviewed previous studies piloted by others on a specific interest. Andrews et al. (2012) and Long-Sutehall et al. (2010) asserted that secondary analysis of archived data is an effective method to analyze an unreachable sample data when dealing with sensitive issues of a study, in order to reach an indefinable or small research population. Andrews et al. (2012) conducted a secondary analysis of archived data using a classic grounded theory and explained that secondary analysis of archived data "enhance quality control by adding transparency, trustworthiness and credibility of original research findings" (p.3). In addition, the reliability of data use is verified through ethical concerns such as copyright, ownership of data, and confidentiality (Andrews et al., 2012). Furthermore, through secondary analysis of archived data, I can easily obtain data that are carefully and consistently collected and archived by the primary research team most closely associated with the variables in my study. The method is time-convenient and cost-effective, and targeted variables are coded, making the data flexible to access (Johnston, 2014). From the literature reviewed in the paper, many research studies have used secondary data analysis in understanding medical errors and their frequency, categories, typology, causes, prevention, reporting, and epidemiology, including issues in patient safety in diverse hospitals and clinics.

Use of secondary analysis of archived data for medical error research. Tam et al. (2005) conducted a systemic research review to access the frequency, type, and clinical importance of medication history errors at hospital admission using secondary analysis of archived data from published studies containing quantitative results of targeted variables. The study was successful, finding that medication history was clinically important. My interpretation of the study revealed that medication history errors are common, though unintentional, in the hospital because there were 67% reports of error cases. The results revealed the clinical importance of medication history reports in hospitals for improved patient safety practices.

Baker et al. (2004) examined the adverse events of unintended injuries and complication incidences among patients in Canadian acute care hospitals by reviewing a random sample of charts of specific patient population at targeted hospitals for the specified year. The study identified a significant AEs prevalence in the charts reviewed. My interpretation of the study result was that the statistical computation of the AEs rate is 7.5% of 2.5 million annual admissions, or 185,000 cases of AEs. Based on the result, the ratio of AEs in patient admission is 1:10, showing an important indication of patient safety improvement (p. 1678).

Vincent, Neale, and Woloshynowych (2001) conducted a retrospective review of AEs in two British acute care hospitals using medical and nursing records. The study result identified a moderate or greater disability or death and an increased percentage of AEs at 10.8% of 110 patients studied. The study confirmed that there is a statistically significant AE incidence in the targeted hospital, resulting in longer hospital stays and higher cost for patients and providers.

Further, Long-Sutehall et al. (2010) pointed out that through secondary data analysis, current and historical attributes and the behaviors of individuals, groups, and organizations can be defined (p. 336). De Vries, Ramrattan, Smorenburg, Gouma, and Boermeester (2008) explored the link between personal or provider characteristics and medical error. The authors conducted a retrospective systematic review study to gain insight into the overall situation in hospital adverse event. Data on incidence, preventability, effect, provider of care, location and type of AEs were obtained according to classification of event. The authors explained that the review comprised studies from the United States and other countries, and found that the definitions of AEs were consistent but the types of errors varied. The result of the study presented an overall incidence of in-hospital adverse events. The authors concluded that because the majority of AEs occur in surgery, patient safety intervention targeting those events would make a big difference in health care.

Gaps in Literature

Through my literature review I identified a gap in the literature with respect to the methods used to identify and report errors, as well as a lack of consistent definitions of errors and its various types (due to lack of descriptive tools such as error coding). The gap was linked to poor information and communication among practitioners and personnel who are authorized to identify and report errors. There is a need to identify other measures to account for and report errors, including the improvement of work safety culture for proper error reporting. Error reporting and disclosure are often used interchangeably and both have been used in the literature in connection with error reporting. Both terms are important to patient safety, and they serve as a means to reveal the occurrence of errors between provider, patient, and the public.

Wolf and Hughes (2008) examined the reporting of health care errors and described "reporting as providing accounts of errors and near misses through verbal, written, or other form of communication, and disclosing as sharing with patients and their families actual errors and near misses" (para, 1). The authors argued that "disclosure of health care errors is not only another type of error reporting, it is also an account of a mistake" (para, 28). Wolf and Hughes (2008) further explained that errors may or may not harm patients but reproduce many problems in the health care system. Reporting both errors and near misses are the key to improving patient safety in healthcare. As such, Wolf and Hughes (2008) stated that the "definitions of reportable events varied by State, bringing hospital leaders to call for specific, national definitions of errors" (para, 4). The authors concluded that voluntary reporting may increase errors and near misses rates, thus providing evidence for the elimination of the blame or shame patterns in safety culture system. Gallagher et al. (2006) stated that "little is known about how physicians approach disclosure, and it involves their attitudes and behaviors that are poorly understood." In addition, multiple barriers, such as fear of lawsuits, shame, and lack of disclosure training, are linked to the gap (Gallagher et al., 2006). Regardless of the efforts of many health organizations to reduce the occurrence of preventable errors, "still not known are the views and support of practicing physicians and the public with regard to both deaths rates due to errors and the proposed change recommendations of national groups for reducing these errors" (Blendon et al., 2002). Even though other researchers have examined other provider characteristics as a strategy to measure medical errors occurring in hospital settings, I did not find any research specifically assessing the association between physician characteristics and surgical errors.

Addressing the Literature Gap on Medical Error

The findings of my study may lead to a better understanding of the causes and effects of errors, as well as patterns, definitions, and types of errors, that account for high rates of surgical errors in the U.S. that are associated with physician characteristics. It was hoped that identifying the factors associated with surgical errors in hospitals would lead to prevention and patient care services improvements through shared information and communication in the hospital workforce. My study has yielded information that may help to improve medical error reporting rates. This study can also provide greater insights for researchers (for observations), health care organizations (for work system practice), and policy makers (for patient safety laws) on the importance of considering the relationship between physician characteristics and surgical errors as a measurable method to identify surgical errors, in the hope that interventions can be developed to prevent errors by working with those physicians who might be more likely to commit the surgical errors.

Definition of Terms

The terms I used in this project are defined as follows:

Close call: A hardly positive escape from a challenging or risky condition (Merriam-Webster, n.d.).

Demographics: These are set qualities of a specific group of people, such as age, sex, ethnicity, race, etc. (Merriam-Webster, n.d.).

Litigation: The procedure of resolving disputes by filing or replying to a complaint through the public court structure (Cornell University Law School, n.d.).

Location of practice: A site occupied for the continuous use of a profession (Merriam-Webster, Incorporated, 2015).

Medical error: Errors or mistakes that are committed by health professionals that result in patient harm (RES Inc., n.d.)

Physician: This is precisely a skilled health-care professional who is trained and licensed to practice medicine such as a doctor of medicine (Merriam-Webster, n.d.).

Physician characteristics: The various attributes of a physician, including skills, year of graduation, practice state, work location, specialty, practice outcomes, and physician demographics (Georgia Board for Physician Workforce, n.d).

Practice outcomes: An event that occurs as a result of a professional activity or process during (Merriam-Webster, n.d.).

Size of hospital: The largeness in number of hospital patient admission (Merriam-Webster, Incorporated, 2015).

Specialty: This is an individual's area of study or profession he/she has distinctive knowledge of (Merriam-Webster, n.d.).

Surgical error: This is a preventable mistake/error during surgery (Nolo, 2015).

Underreporting: These are some issue, event, statistic, and others that a designated authorized reporter, such as individuals, agencies, has reported less than the factual number (Merriam-Webster, n.d.).

Work location: This is a place of work where employed people undertake their job duties. It is also used to determine the employee's economic characteristics, such as profession, organization, and employment status (OECD, 2001).

Year of graduation: The year the physician graduated from medical school.

Assumptions

In order to conduct my study, I made the following assumptions: first, secondary data analysis of archived data is a reliable, valid, measurable, and consistent method for a research study. I assumed that the original data collection retrieved from my study was completed in a thorough and rigorous manner by the original researchers and that the data had been maintained properly and was relevant to my study. Second, I assumed that the observed data was generalized of the population studied.

Scope and Delimitation

The intent of this study was to examine if there was an association between physician characteristics and occurrence of surgical errors in hospitals. I incorporated the analyses of secondary archived data by identifying physician characteristics and observing trends of surgical errors reported of practitioners by hospitals from the data source used for the study. The delimitation of my study was the selection and use of a closed format data that would not allow me to produce any additional information from the population studied. Also, an in-depth exploration of the causes of the surgical errors, while important, was beyond the scope of this study.

Significance

The focus and purpose of my study was to explore the relationship between physician characteristics and surgical errors in U.S. hospitals. My proposed research study helped to fill the gap in understanding provider characteristics that may be associated with surgical error incidence. The importance of my study is that it would help improve patient safety practice by identifying physician characteristics that may help predict errors. Also, it may assist in understanding practitioners' behavior patterns that may need to be modified that hinders physicians from reporting preventable adverse events. The study may help create a change in work culture toward a collaborative work environment to reduce surgical errors and its damaging effects on patients and health care providers.

Summary and Conclusion

In summary, in Section 1 of this proposal I described the problem of underreporting of medical errors and surgical errors in U.S. hospitals. I also identified the gaps in the methods used to identify and report these errors, including issues of lack of consistent definitions of errors and various types of errors. Moreover, I discussed the type of study I proposed, a quantitative correlational study that measured the association between the independent and dependent variables using secondary analysis of archived data. The reviewed literature helped to understand the patterns and nature of medical and surgical errors or adverse events occurring in the hospitals. Observing proper medical and surgical error reporting for patient safety in a hospital setting is complicated and consists of many strategies and practices. However, errors have been identified as a major patient health care crisis in hospitals locally and globally, and they are underreported due to many reasons, including lack of agreement in methods of identifying errors, inconsistent definitions of medical and surgical errors, poor surveillance, poor documentation or voluntary reporting, hospital culture or punitive environment, system issues, poor teamwork, and lack of communication.

Diverse research has been conducted on medical and surgical error matters for hospital patient safety, and operational issues have been identified. The literature review illustrated methods to promote patient safety culture and prevent errors caused by system and latent failures in hospitals through error tool data. Moreover, identifying the strategies that have successfully helped to observe and report errors for patient safety improvement has provided for a good understanding of what was required to improve error reporting for patient safety health care practice by physicians and other health professionals.

In conclusion, through the literature review in this section of the study, I identified the need to examine further strategies that can support the appropriate reporting of medical errors. I established the use of secondary analysis of archived data as a reliable data tool for the variables in this study. Further, promoting patient safety of health care for surgical patients requires proper counting and reporting of the errors incidence, including the problems and describing the epidemiology of those adverse events complications. Most importantly, the human, systems, and environmental barriers to proper error reporting should be clearly addressed by health care organizations, which would help create a social change toward improving patient safety in hospitals**.**

The potential social change impact of my study is that better understanding of the nature of surgical errors occurrences enabled by proper accounting and reporting of errors may guide the development of future policy and procedures to prevent unintended harm and adverse outcomes among patients. Section 2 of the study proposal explains the methodology of the study, including the study design, data collection, population and sampling, and the study evaluation plan.

Section 2: Research Design and Data Collection

According to research, medical errors are underreported, leading to concerns for patient safety due to the high rate of injuries and deaths attributed to them (Wolf & Hughes, 2008, para. 2). Most people receive inpatient or outpatient treatment at some point in their lifetime for treatment and care of an illness or disease. Medical or surgical errors are mistakes that can happen in a surgical operating room or before or after surgery. For example, surgeons can perform the wrong surgery on the wrong part of a patient's body or operate on the wrong person, surgical instruments can be left in patients' bodies, and wrong doses of anesthesia can be administered to a patient.

Medical or surgical error is defined as "a preventable mistake or adverse effect of care, whether or not it is evident or harmful to the patient mistake during surgery" (Nolo, 2015, p. 6). According to an Institute of Medicine (IOM), "an estimated 98,000 patient adverse events (PAE) cause mortalities in the country each year" (as cited in The Advisory Board Company, 2015, para. 2). The number of adverse events, including surgical errors, that occur in U.S. hospitals each day is approximately 118,000, even though this number represents incomplete medical records, as only one in seven hospital errors is reported (The Advisory Board Company, 2015). Research points to the need for proper counting, reporting, or identification of medical error occurrences (The Advisory Board Company, 2015, para.6).

According to reports, these errors are underreported or not charted. As described in the literature review, researchers have examined communication issues among physicians, patients, and hospitals staff authorized to monitor error events that prevent reliable and comprehensive collection of data on medical errors (Wolf and Hughes, 2008). Researchers have also examined techniques used in measuring errors such as error mitigation and practice, for example, Van Den Bos et al. (2011) used actuarial approaches such as medical claim data to identify and measure the frequency and cost of health care services attributed to medical and surgical errors, and found errors not previously reported. However, there remains a lack of study on personal provider characteristics by researchers as a measure of identifying and reporting errors.

Examining provider characteristics not only supports the identification of medical errors for reporting, it also aids in understanding the causes and patterns of error incidence in hospitals that may improve medical practice and patient safety. The purpose of this study was to examine the association between physicians' characteristics and surgical errors in U.S. hospitals. The intent of the study was to generate knowledge that may help in understanding the relationships between physician characteristics and surgical errors, which may lead to improvements in prevention, accounting, and documentation of medical errors in the United States.

In this section, I describe the study design and rationale, methodology, data management (population under study, sampling design, and data collection procedures), operationalization of variables, data instrumentation (reliability and validity), ethical concerns, and data analysis plan. The section includes a description of the quantitative and retrospective cross-sectional (descriptive and inferential) design study, including how the approach was used to test the hypotheses and answer the research question. I used data from the National Practitioner Data Bank (NPDB) as my data source. NPDB is a de-identified public use data set that contains information on specific variables taken from Adverse Action Reports and Medical Malpractice Payment Reports on licensed health care practitioners and other pertinent entities. The data set is updated on a quarterly basis and is intended to provide data for statistical analysis (Health Resources and Services Administration [HRSA], 2016).

Research Design Method and Design Appropriateness

I conducted a quantitative correlational study to examine the relationship between selected independent variables and a dependent variable. This study was a secondary analysis of archived data retrieved from the NPDB. My independent variables were physicians' work state, home state, state of license, field of license, age group, and graduation year group. My dependent variable was any surgical error for the total number of cases representing patients in the national data set (NPDB, 2015).

The preferred method was appropriate for the study because the aim of a quantitative research study is to determine the relationship between variables (University of Southern California, 2016). Quantitative methods are appropriate for data collection and analysis because of its rapid time and efficiency. There is the possibility of using previous studies to investigate new ideas with a productive reasoning (Le Roux & Vidal, 2000). Furthermore, quantitative methods are suitable for conducting analysis and measurement of numerical data, including descriptive and inferential statistical procedures (Creswell, 2009). There is a high level of reliability of collected data because of controlled observations, mass surveys, or other specific research and data manipulations. This reliability allows for assessments with larger populations, including the reduction of ethical concerns (e.g., data privacy and security) associated with primary data collection (Matveev, 2002; Substance Abuse and Mental Health Services Administration [SAMHSA], 2016).

The research questions and hypotheses that guided the study are as follows: 1. Research question: What is the association between physician work state and occurrence of surgical errors?

1a. H0: There is no association between physician work state and occurrence of surgical errors.

1b. H1: There is an association between physician work state and occurrence of surgical errors.

2. Research question: What is the association between physician home state and occurrence of surgical errors?

2a. H0: There is no association between physician home state and occurrence of surgical errors.

2b. H2: There is an association between physician home state and occurrence of surgical errors.

3. Research question: What is the association between physician state of license and occurrence of surgical errors?

3a. H0: There is no association between physician state of license and occurrence of surgical errors.

3b. H3: There is an association between physician state of license and occurrence of surgical errors.

4. Research question: What is the association between physician field (specialty) of license and occurrence of surgical errors?

    4a. H0: There is no association between physician field (specialty) of license and occurrence of surgical errors.

    4b. H4: There is an association between physician field (specialty) of license and occurrence of surgical errors.

5. Research question: What is the association between physician age and occurrence of surgical errors?

    5a. H0: There is no association between physician age and occurrence of surgical errors.

    5b. H5: There is an association between physician age and occurrence of surgical errors.

6. Research question: What is the association between physician graduation year and occurrence of surgical errors?

    6a. H0: There is no association between physician graduation year and occurrence of surgical errors.

    6b. H6: There is an association between physician graduation year and occurrence of surgical errors.

Methodology

Population, Sampling, Data Collection Methods, and Rationale

Population. The target population was U. S. physicians, and the cases were occurrences of surgical errors of practicing physicians throughout the 50 U.S. states. The NPDB data set contained 1,180,177 cases at the time of the study. Fifty-four variables covered the entire country relating to the problem of study. The study population that was used to generalize the entire population was not easy to identify. The study population was determined by using a sampling technique to execute the sample size calculation. However, the inclusion and exclusion of population (cases) elements to be observed were precisely defined and clearly stated to ensure the study sample used will make representative inferences to the population (cases) observed. The rationale for choosing this population was because the targeted population for the study was practicing physicians, and the focus was to examine surgical errors that affect patient safety.

Sampling frame. For this study, I recruited no participants because all data sets and data analysis were based on secondary archived NPDB data sets. NPDB is a de-identified public use data set that contains information on specific variables taken from Adverse Action Reports and Medical Malpractice Payment Reports on licensed health care practitioners and others. The primary data of NPDB population (cases) were routinely collected through convenient sampling generated by a voluntary Integrated Querying and Reporting Service (IQRS) on the NPDB website or through an external application.

The data include reports for the 50 states, as well as the U.S. territories, Puerto Rico, the Armed Forces, and other territories (USDHHS.HRSA, 2015). The database dictionary defined the variables of interest by providing a clear description of what was being demanded including all data elements that appear in the data submission files with their numeric references to the file and their existing location. Moreover, all data elements have subsequent definitions or references to confirmation tables. The NPDB collects and maintains reported information submitted by eligible entities and authorized agents (e.g., a risk manager who is chosen and empowered by a registered entity [hospital] to report to a higher database). The NPDB data set was reliable because it is the most comprehensive source of malpractice payment data presently accessible in the United Stateas, and it is the only data source for claim payments for the 50 states (Guirguis-Blake, Fryer, Phillips, Szabat, & Green, 2006).

The sampling frame from the data set consisted of 1,180,177 cases and 54 variables of adverse events and physician characteristics that met the criteria for inclusion of medical and surgical error cases that were relevant to the study. Seven out of the 54 variables listed in the data set were used for analysis. I used six variables to represent the physician characteristics of the physician population (units) in the data set to make observation for the study, including the selected variable used to represent the outcome of surgical error: malpractice allegation group. This population selection was proper for the study based on the gaps identified in the literature review.

The selected independent variables included specific elements describing physicians' characteristics, while the selected dependent variable was used to fulfill the goal of the study. The selected outcome variable contained all elements described as surgical errors. The independent variables were the predictor variables that measured the dependent (outcome) variable (medical or surgical error). Moreover, to achieve the study purpose, the selected variables were related to the problem of study.

In addition, a sample population (cases) would be more convenient to analyze data more conveniently to generalize to the entire population. Lastly, it is important to calculate a good estimate of the standard error.

Data access/procedure. The study data source, NPDB, is a large archived public use data set designed for statistical analysis purposes. The data set is readily available online and can also be downloaded. The data are defined by coding and are de-identified to prevent any ethical violations regarding patient privacy and to enable researchers to retrieve needed information without further approval from the host site/data set owners (USDHHS.HRSA, 2015). After reviewing the data set, I imported the required data for my study into an Excel spread sheet and saved them as a named file in my computer. Next, I conducted a data review of the selected data and created a data dictionary, data table, and data measurement of variables to be certain that the collected data were the ones needed for the study. Furthermore, I conducted a descriptive analysis of the data set to confirm its accuracy, identify any missing data, and examine skewness, kurtosis, and outliers for addition, removal, or correction.

Sample size. I did not need to calculate a minimum sample size because the data set was very large and the data had already been collected. I sampled my cases directly from the data set as proposed in the data collection section of the study. The data set is a quantitative archived data set that contains information of my target population (cases) that would be generalizable to the population studied. Moreover, I included a minimum sample size calculation to confirm the minimum sample size needed for data analysis. After using a sample size software to compute the sample size, I found that I needed 385 cases for the study.

I used the Raosoft (2004) software to calculate the sample size; it calculated the sample size by computing the 1,180,177 data cases, confidence interval (95%), and margin of error (.05%). The confidence interval was measured in percentages (confident levels), which indicated the probability with which the value of the sample mean was equivalent to the value of the population mean. I estimated the range of upper and lower statistical values that were reliable with the observed data and were likely to contain the actual population mean (Creswell, 2009, p.166), and the confidence level indicated how certain the validity and reliability of my data set were within its margin of error. Common standards used are 90%, 95%, and 99%. Most researchers use the 95% confidence level to calculate the sample size (Raosoft, 2004). These numbers are considered to be valid for the selection of a study sample using random sampling (Delice, 2010).

Furthermore, my data set was a large and can be generalized to the population. I used G*Power to clearly determine how many total cases I would need for the multiple logistic regression design that was selected to compute the study outcome analysis. I computed in G*Power the z test and logistic regression for the minimum sample size and power by selecting the Wald test for large sample approximation to further validate my sample size selection and result from the other procedures used to compute sample size from the study data cases (population). The result was a 0.95 actual power and 337 sample size (Heinrich-Heine-Universität Düsseldorf, 2016). Also, the actual 1,180,177 data cases were added in computation.

The result, though not giving the exact values in each procedure used for sample size verification, showed that they are connected to the expected value of sample size (see Illustration B; Figure 2 and 3.

Illustration B. G*Power Sample Size Computation **z tests -** Logistic regression

Options: Large sample z-Test, Demidenko (2007) with var corr

Analysis: A priori: Compute required sample size

Input:	Tail(s)	= Two
	Odds ratio	= 1.5
	Pr(Y=1|X=1) H0	= 0.5
	α err prob	= 0.05
	Power (1-β err prob)	= 0.95
	R^2 other X	= 0
	X distribution	= Normal
	X parm μ	= 0
	X parm σ	= 1
Output:	Critical z	= 1.9599640
	Total sample size	**= 337**
	Actual power	**= 0.9500770**

Adapted from Heinrich-Heine-Universität Düsseldorf (2016).

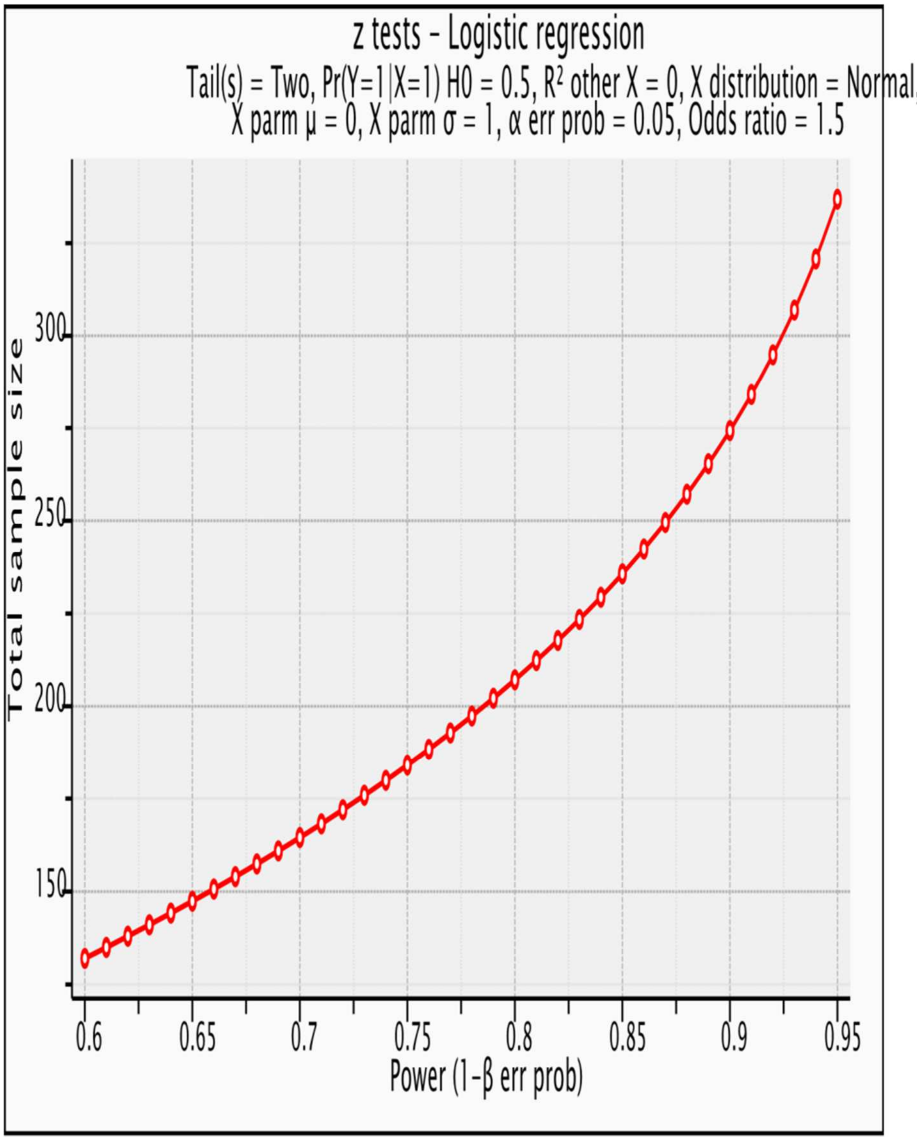

Figure 2. G*Power Sample Size - i. Note. Reprinted from Heinrich-Heine-Universität Düsseldorf

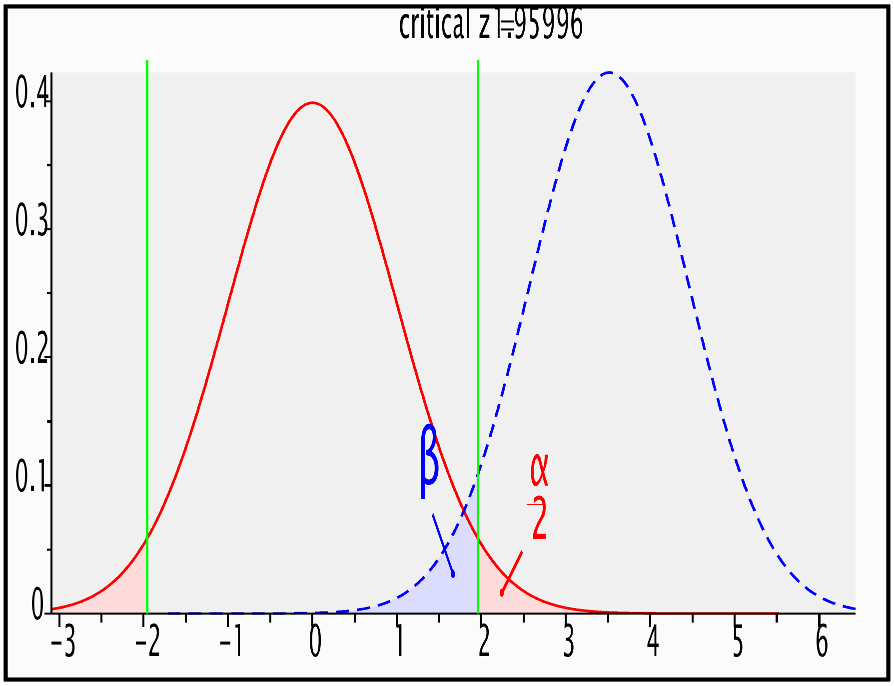

Figure 3. G*Power Sample Size - ii. Note. Reprinted from Heinrich-Heine-Universität Düsseldorf (2016).

Data collection method. The study population I observed was for hospital physicians all over the U.S. relating to their professional competence and conduct, and the sample size was the units of the cases of selected variables to be studied. The study was a quantitative research design, and the data were already collected and comprised a total of 1,180,177 cases from 1990 to 2015 (NPDB, 2015). I generated the 2015 data sample and added it to the condensed overall data set for analysis using data manipulation strategy in SPSS. I choose to analyze the six independent variables and one dependent variable I identified in my proposal (please refer to the sampling frame section). In reference to my literature review, medical error according to research had been recorded dating back to the 1960s and acknowledged by the pubic (AHRQ, 2015). Researchers have conducted numerous studies to identify and estimate medical errors incidences at different time intervals. For instance, between 1990 and 2010, researchers found that their estimates on medical error were low (Makary et al., 2012). Also, a hospital rating organization 'Healthgrades', conducted an evaluation of the nation's hospital quality outcomes for 2013 and reported the rates of errors they identified from 2009 through 2011(Healthgrades, 2016).

The NPDB data set covers 50 states of the U.S. from September, 1990, to March, 2015, with 1,139,649 cases and 40,528 newly added cases. In this study, I analyzed the entire sample from 2015, including the newly added cases. The reason for the data set year selection was that information revealed in the literature review described that between 1990 and 2013, researchers have examined related data, so it may be reasonable to examine current data of the problem to make observation for identifying errors, including other reasons such as checking continued trend and rates in errors occurrences.

Data Analysis Plan

I performed my data analysis by conducting the following operations on the data set (variables and statistical procedures): conducted selected descriptive statistical analyses using SPSS-frequencies (measures of central tendency); calculated percentages; summarized the numerical results with descriptive analysis tables or graphs, including my interpretation; conducted selected inferential statistical analyses using SPSS-Bivariate: Chi Square correlation, cross tabulation, and Pearson's correlation; calculated multivariate logistic regression; and summarized the numerical results with inferential analysis tables or graphs, including my interpretation. The statistical tests, described below, are selected based on the number of variable selected, the types of question stated, the type of measurement sought from the variable observed, and data distribution (see Tables 1 and 2 in the Appendix). The planned procedure will be carried out for the outcome variable.

Preparing the data for analysis. Because of the implication of the validity and reliability of the data set for the study outcome, the first data management I performed before the data analysis was to screen or review my selected data sample to identify potential pattern of or any missing data and outliers from the data to be observed (missing values, out-of-range values, etc.). Following the review, if there were missing data from any of the data set cases, I examined the data sample(s) to see if patterns exist in the missing data. Because less than 5% of data were missing, I deduced that the data were missing by chance rather than because of systemic errors and substituted a mean value for that variable missing data, I handled outliers in my data set identified as a result of an error or a false measurement by simply removing them. In addition, the process of identifying missing data was performed using the statistics tool box in spss -analyze --> descriptive statistics --> frequencies, or by using the missing value link to obtain the number of missing values for each variable (California State University, Northridge, n.d). Also, outliers are case scores that are extreme and this would have a high impact on the outcome of my study statistical analysis if found in my data set. Therefore, to avoid biased results, the data set must be screened for both univariate outliers on one variable alone and multivariate outliers on a combination of variables. Outliers can be screened by following spss link-analyze --> descriptive statistics --> explore, and click “outliers.”

Lastly, there are various convenient methods to perform these measurements (CSUN, n.d).

Descriptive analysis. Descriptive analysis was used to describe the population being studied. I conducted a descriptive analysis with SPSS by computing a frequency statistics to measure frequency for measures of central tendency (mean, mode, median) to summarize a group of scores with a single number, and dispersion for standard deviation and range that helped determine the spread of scores within a group of scores, so that I can conclude the reliability of the data—larger number data are spread out and smaller number data are grouped together (Kent State University, 2014; Crossman, 2014).

Inferential analysis. An inferential analysis was used in making inferences about the population from the observation and analyses of the sample (Kamin, 2010: Crossman, 2014). It was good to compare the data with ideas and theories to see how well they matched through calculations such as variance, standard deviation, sum of squares, and calculated test statistics. The steps in hypothesis testing was conducted with this process: calculate the test statistic; state the given probability of a Type I error; calculate the degrees of freedom; and draw a conclusion based on the calculated test statistic (the region of rejection (RR) to accept or reject the null hypothesis and to calculate the p value) (Kamin, 2010; Crossman, 2014).

The inferential statistics I used for the study included both bivariate analysis and multivariate logistic regression analysis. I started with the bivariate analysis using cross tabs and chi square. Cross tabulation was a frequency statistics that displayed the relationship between two variables in a single table. It computes the “Phi Cramer's V” measures of association to calculate the strength between one nominal variable with other nominal variable, and the Pearson chi-square test, essentially a correlation test for categorical variables to tell if they are statistically significant (Illinois State University, 2015; University of Toronto, 2015). The correlations yielded the Pearson correlation coefficient(r), a measure of linear association between the variables (IBM, 2015). Following the computation of the bivariate analysis, the “Multivariate Logistic” regression analysis was computed in SPSS to explore correlation by predicting the value of a variable based on the value of another variable (Lund Research, 2013).

The “Multivariate Logistic” regression model was a statistical technique used for modelling and analyzing the effect of multiple independent variables (the predicting criterion) on a dependent variable (outcome). In this study the dependent variable was not a continuous or quantitative variable; conversely, it was a discrete or categorical variable that has two values, making the model suitable to make correlation in the study. In addition, the model gave specific probabilities of the actual outcomes for each case involved (Mertler & Vannatta, 2005, p. 313). The syntax and output files in SPSS were generated, and different kinds of chart were used to describe the data.

The mock tables for the study included one general table showing the overall data analysis plan (see Table 3 in the Appendix), two descriptive stat mock tables for bivariate analysis (see Table 4 in the Appendix), and one inferential statistic table, which is multiple log regression (see Table 5 in the Appendix).

Validity Issues

An essential part of a research study is the quantification of the elements (study sampling). These elements are measured through instruments or experimental methods to reduce possible errors that may pose threats to the validity of the research (Drost, 2011).

Validity in a research is defined as an estimate of the extent by which research data, tests, or methods actually measure or reflect what it is intended to measure or reflect (Newman, 2008).

In every research study, there are many threats to the study validity that may question the study's capability to conclude an effective outcome; therefore, it is important to identify them to prevent them from occurring (Creswell, 2009, p.162). In a quantitative research design, issues in validity make a contrast between an extraneous variable and a confounding variable (University of South Alabama, 2016).

- Extraneous variable: these are variables that may contend with the IVs to make clear the outcome of a study.
- Confounding variable: these are third variables that have a relationship with the IVs and DVs. Also, is a variable that systematically impacts the IV and DV. (University of South Alabama, 2016)

There are two types of threat to validity: threats to internal validity and threats to external validity (Creswell, 2009). The possible threats to validity in this study are described below.

Threats to internal validity. Internal validity is the degree to which a researcher concludes that his study precisely reflects what he is observing. Threats to internal validity are research procedures and other factors that can obstruct the researcher's ability to make correct inferences from observed population in a study, i.e., that a relationship exists between the independent and dependent variables (Creswell, 2009). There are diverse threats to internal validity, and one possible threat to internal validity in my study was that I have no control over the original study. Therefore, the issue of instrumentation may arise because the present study is a secondary archived data set, and it is constantly updated at intervals annually. As a result, the data may present change in the scores on the independent and dependent variables in data accounting during data collection. I addressed this issue in this study by monitoring the periods when my data source published an updated version of my proposed study data to ensure that I was measuring a reliable data set that did not affect the internal validity of my study findings.

Threats to external validity. External validity is the ability to generalize the study results to the study sample, which is an important concept in a quantitative research. The issue of threats to external validity occurs when a study draws incorrect sample data from the sample data to other populations or situation (Creswell, 2009). The threat to external validity my study may have as a secondary data analysis was that the study data may be neither valid nor reliable. As such, I have strong confidence that my external and future validity are very low.

However, the issue of population validity is the ability to generalize the study outcomes to people or populations not included in the study (University of South Alabama, 2016), which may arise in this study. Unacceptable sampling method may affect data analysis by causing a bias in generalizing population in the study result. The data used a convenient sampling method, which may limit my external validity, because my data analysis may not apply to physicians in other hospitals. Also, the data were reported through a voluntary mechanism, which may be different and may limit my outcome to a certain degree. Another issue was the possibility of the data not being capable of answering the research questions because the data were collected for some other reason, even though the data set contained elements needed for and related to the current study. I addressed this issue by conducting data screening to examine missing data and outliers for each variable imputed in the data set.

Ethical Procedures

The data source for my study was from National Practitioner Data Bank (NPDB), maintained by the Health Resources and Services Administration (HRSA) of the U.S. Department of Health and Human Services (USDHHS). This data source's policies and regulations on the primary data reporting, collecting and storage already addressed any ethical issues of human protection, security/privacy for the primary data as data sets published over the internet were coded and de-identified (USDHHS.HRSA, 2015).

Although Tripathy (2013) suggested that public use data sets found free on internet require permission for further use and analysis, this did not apply to my data set because, according to the data set owners, USDHHS/HRSA/NPDB, the data is prepared for public use and does not require permission to access and analyze. I sought approval from the Walden University IRB before analyzing my data. On approval of the IRB, I proceeded to obtain my proposed data set from the owners' databank found at the USDHHS/HRSA/NPDB website. Once I accessed the data set, I conducted the procedures necessary to sample my population and study data, and conducted the various analyses for my study. Subsequent to accessing and obtaining my data set, I ensured that ethical regulations governing confidentiality and security of NPDB information were strongly observed. Also, collection and manipulation of data standards was conducted in adherence to ethical regulations that prevent falsifying of data set information. After concluding the data analysis, I reported only the de-identified data.

The data set remains the property of the USDHHS/ HRSA/NPDB. Moreover, the study outcome would be shared with Walden University research center, consequent to being published, and the study outcome would be shared with researchers, public individuals, and entities that have an interest in patient safety, and with the USDHHS/HRSA/NPDB upon request.

Summary

Provided in Section 2 were an outline of the current study research design (Cross-sectional quantitative method) and details of the rationale of using secondary data (SAAD) to assess the strength of association between physician characteristics and surgical errors in U.S. hospitals. The purpose of the current study was restated and the study questions and hypotheses were repeated. The sampling procedures (random sampling) and tools applied toward selecting sample size were also described, including defining the study population, the independent and dependent variables, and data management performances. The threats to internal and external validity of the study were also discussed. The statistical process of the data analysis method of the study (multiple logistic regression) was described, and the plan for descriptive and inferential data analysis to test hypotheses and answer research question was explained. Also, in this section, I addressed the ethical considerations for the procedures of the study.

The objective review of the results and findings of the data collected for the study is presented in the next section (Section 3) of this project.

Section 3: Presentation of the Results and Findings

The purpose of this study was to quantitatively explore the association between selected physician characteristics and surgical errors in U.S. hospitals. The physician characteristics included physician's work state, home state, state of license, field of license, age group, and medical school graduation year group. The dependent variable was surgical error classified by malpractice allegation type. The data for the analysis was from the National Practitioner Data Bank (NPDB) administered by the Health Resources and Services Administration (HRSA) of the U.S. Department of Health and Human Services (USDHHS.HRSA, 2015). After data sampling and management, I used multiple regression (binary logistic regression) analysis to assess the association between the final selected physician characteristics and occurrence of surgical errors.

The main research question was this: What is the association between physician characteristics (independent variables) and surgical errors (dependent variable)? The null and alternate hypotheses of physician home state (independent variable) and surgical errors (dependent variable) are as follows:

1. Null Hypothesis (H0): There is no association between physician home state and surgical errors.

   Alternative Hypothesis (H1): There is an association between physician home state and surgical errors.

The null and alternate hypotheses of physician state of license (independent variable) and surgical errors (dependent variable) are as follows:

2. Null Hypothesis (H0): There is no association between physician state of license and surgical errors.

   Alternative Hypothesis (H2): There is an association between physician state of license and surgical errors.

The null and alternate hypotheses of physician field of license (independent variable) and surgical errors (dependent variable) are as follows:

3. Null Hypothesis (H0): There is no association between physician field of license and surgical errors.

   Alternative Hypothesis (H3): There is an association between physician field of license and surgical errors.

The null and alternate hypotheses of physician age group (independent variable) and surgical errors (dependent variable) are as follows:

4. Null Hypothesis (H0): There is no association between physician age group and surgical errors.

   Alternative Hypothesis (H4): There is an association between physician age group and surgical errors.

The null and alternate hypotheses of physician age group (independent variable) and surgical errors (dependent variable) are as follows:

5. Null Hypothesis (H0): There is no association between physician medical school graduation year group and surgical errors.

   Alternative Hypothesis (H5): There is an association between physician medical school graduation year group and surgical errors.

Section 3 includes a description of the data collection process and time frame through which NPDB data were collected, a review of the sampling methods and study framework, how participants were recruited and cases documented, and any discrepancies in the data collection process. I describe the basic descriptive statistics such as the frequencies, percentages, and measures of central tendency (i.e., count, mean, median, minimum, maximum, standard deviation). I also report the results of the inferential statistical analysis.

Data Collection

NPDB Data and Secondary Data Set

NPDB is a de-identified public use data set that contains information on specific variables taken from Adverse Action Reports and Medical Malpractice Payment Reports on licensed health care practitioners and others. According to the NPDB, the data include reports for the 50 states, as well as the U.S territories, Puerto Rico, the Armed Forces, and other territories (USDHHS.HRSA, 2015). NPDB data are collected on an ongoing basis through convenient sampling generated by a voluntary Integrated Querying and Reporting Service (IQRS) on the NPDB website or through an external application called the Querying and Reporting XML Service (QRXS). In the QRXS process, the reporting entity stores and manages practitioner data within its information or credentialing systems. Through the QRXS it is easier to integrate NPDB information into the entities that established data systems (USDHHS.HRSA, 2015).

A total of 1,180,177 cases of medical errors and 54 variables were collected from 1990 to 2015. The clinicians included in the data set are physicians (MDs and DOs), dentists, pharmacists, doctors of nursing practice, psychologists, chiropractors, and podiatrists. This study focused on selected physicians' characteristics. The variables of interest were included in the NPDB data set; there were no discrepancies between the data plan presented in Section 2 and my analysis of the data in this section.

Sampling and Time Frame

After gaining approval from the Walden's Institutional Review Board (05-25-

160511681) to analyze data, I downloaded the data set from the NPDB website into SPSS. The selected variables were compiled in a separate SPSS spread sheet, keeping only the relevant variable for the year required for this study. I used the 2015 data set and seven variables to obtain my study sample.

I sampled my cases directly from the data set as described in the data collection section of the study. There was no need to calculate a minimum sample size because the data set was very large and the data had already been collected. However, a minimum sample size of 385 cases would be needed to conduct my analysis.

Data sampling and analysis were completed from June 1 to July 13, 2016. I focused on the 50 U.S. states and District of Columbia. I chose U.S. mainland states because their hospital systems are adequately monitored by government health departments and guided by their health policies. Because I was conducting my research based on a secondary archived data set, I needed to restrict my data to surveys concerning my study problem and target population reported by trusted health and research organizations, or entities that monitor the progress of health care practices in the United States. I did not include the U.S. territories in my study because they were not within the scope of the study. This helped me avoid reliability issues that may have arisen from using data from hospitals not monitored by U.S. agencies.

Data Preparation

Missing Data

As the data were categorical in nature (string variables), the available algorithms for handling missing values of numerical variables were not used because no statistical software could fill in categorical missing data unless they were linked to other data, so all missing data were removed from the data if they were "less than 15% of the counts and would not have much effect on the outcome of the analysis" (Mertler & Vannatta, 2002, p. 37). Further, it was out of the scope of the study to explore other sources of information and fill in missing values. A new variable, geographical region with five geographical levels, was introduced for each state variable. I grouped the variables into regions to conduct a logistic regression analysis. In each of those three new variables, states were transformed into their corresponding regions such as West (W), North East (NE), South East (SE), South West (SW), and Midwest (MW). I grouped the state variables into categories as regions because the design favored the logic regression statistics I used to analyze the study outcome. The logic regression model is designed for analyzing binary and categorical or quantitative response variables (Mertler & Vannatta, 2002, p.17). The data were missing for 13 cases in the variable age group and graduation year group. Because fewer than 5% of cases had missing values, I used the Listwise default to exclude the missing cases (Mertler & Vannatta, 2002, p.36). There were no missing cases in the field of license variable.

The study focus was surgeons. Therefore, I included data from the following specialties: allopathic physician (MD), physician resident (MD), osteopathic physician (DO), and osteopathic physician and resident (DO). The other clinicians, such as dentist, dental resident, nurse practitioner, and doctor of nursing practice, were excluded from the analysis. Finally, because the study addressed only surgical errors, the dependent variable data (malpractice allegation group "alegnnatr") was transformed into a binary variable with two outcomes: "surgical error" and "other or nonsurgical error." I filtered out and excluded labels within variables that were not required for the study, and then created variables that were grouped into categorical variables based on predetermined groups. I ran frequency distribution checks to verify I was correctly conducting the data management procedures.

The final data set that I used for the analysis consisted of 2,765 cases of surgical error, five independent variables (practitioner's home state, license state, age group, graduation year group, and field of license), and one binary dependent variable (surgical error).

After excluding missing cases and other cases that were not within the scope of the study, I found only 1% missing data among the variables of interest and those that met my inclusion criteria required for the study, thereby making the population (cases) representative of the target population. Data were sorted to select only malpractice claims data from 2015. The most significant reason for the 1-year data focus was because I wanted to sample the most recently collected data, making the assumption that these were probably more accurate or valid. The final data set from 2015 consisted of 60,457 cases with only 1 % missing values in most of the independent and dependent variables.

The aim of the study was to identify physician characteristics that may be associated with surgical error occurrences. I selected seven variables (six indicating physician characteristics and one indicating surgical error occurrences) from the full data set of 54 variables. I selected the seven variables based on the research gap identified in the literature. The research gap related to problems in the methods used to identify and report errors and others that are linked to poor information and communication among practitioners and authorized personnel who identify and report errors. The variables I selected for physician characteristics (IVs) were physician's work state, home state, state of license, field of license, age group, and medical school graduation year. I selected the variable malpractice allegation group (DV) to represent surgical errors.

I originally intended to use six IVs for observation, but I narrowed the list to five because I discovered during data management that one IV was highly correlated with another, so I excluded it from analysis. See Table 3below for a list of the variables of interest.

Table **3**

Study Independent Variables and Dependent Variable with Database Codes

Variable Names	Code ID	Types
Physicians home state	homestat	Independent
Physicians state of license	licnstat	Independent
Field of license	licnfeld	Independent
Age group	practage	Independent
Graduation year group	grad	Independent
Malpractice Allegation Group	alegnnatr	Dependent

Correlational Analysis

To avoid issues of multicollinearity in the data analysis, I excluded the variable work state because it was highly correlated with the variable home state .

The justification for exclusion of the work state variable was based on a finding in the reviewed literature that the work environment is acknowledged as an influence in work culture that may contribute to error behaviors (e.g., work policies such as those pertaining to litigation may not benefit physicians who report errors). In addition, error is noted as a universal issue that occurs in different work environments.

I chose the home state variable of the two correlated variables because it was an important factor that could influence error behaviors, and it was correlated with practitioners' individual and biological factors of their behaviors, such as their thoughts about planned action, recognized visible benefits, and knowledge about public health problems. For example, a trained physician of a minority background has a different thought of action compared to a trained physician from a nonminority background. In addition, the workplace variable was intended to address the skill factor of the intrapersonal ecological model defined in the study theoretical framework, but it was replaced with the physician field of license. Because the workplace is where the skill is practiced, the physician field of license was directly correlated with the skill and could be a good attribute used to identify errors among them.

Analysis of Results for Study Sample

Descriptive Statistics

I used SPSS to conduct two descriptive statistical analyses of the sample demographic characteristics. First, I computed total count, frequencies, and percentage in order to clearly define the spread of cases amongst the variables and their categorized values separately. Secondly, I computed the measures of central tendency (minimum, maximum, mean, standard deviation, and mean variable rate) to obtain the central value in the distribution of categorical values measured for each variable case.

A total of 2,765 cases of physician's surgical error reports were obtained from 60,457 cases reported during 2015. See Table 4 below.

The frequencies and percentages of the number of cases contained in each variable are as follows: those aged 80 through 89 have the lowest number of cases (n = 13, 0.5%), whereas those aged 40 through 49 have the highest (n = 793, 28.7%) for the variable age group of practitioner.

In the graduation year group variable, the year category 2010 through 2019 (n = 19, 0.7%) has the lowest cases, whereas the year category 1990 through 1999 (n = 782, 28.3%) has the highest cases of all the categories.

Of the study sample, 91.6% of cases were reported among Allopathic Physician (MD), and 0.1% were reported among osteopathic physician resident (DO) for the practitioner field of license variable. With respect to practitioner home state, 33.9% of cases were reported by those from the Northeast (NE), the highest percentage, and 7.7% were reported by those from the Southwest (SW), the lowest number of cases. Finally, of the variable practitioner state of license, 30% cases were reported by those from the Northeast (NE), the highest percentage, and 12% were reported by those from the Southwest (SW), the lowest percentage.

Table 4

Frequencies and Percentage Distributions of Physician Demographic Characteristics (N = 2765)

Variables ID (Valid)	Frequency (N=2765)	Percent (N=100)
Age Group of Practitioner		
Ages 30 through 39	510	18.4
Ages 40 through 49	793	28.7

Ages 50 through 59	766	27.7
Ages 60 through 69	545	19.7
Ages 70 through 79	138	5
Ages 80 through 89	13	0.5
Total	2765	100

Graduation Year Group		
1950 through 1959	28	1
1960 through 1969	243	8.8
1970 through 1979	533	19.3
1980 through 1989	735	26.6
1990 through 1999	782	28.3
2000 through 2009	425	15.4
2010 through 2019	19	0.7
Total	2765	100
Practitioner Field of License		
Allopathic Physician (MD)	2532	91.6
Physician Resident (MD)	16	0.6
Osteopathic Physician (DO)	215	7.8
Osteopathic Physician Resident (DO)	2	0.1
Total	2765	100
Practitioners Home State		
W	487	17.6
NE	938	33.9
SE	628	22.7
SW	212	7.7
MW	500	18.1
Total	2765	100
Practitioner License State		
W	638	23.1

NE	830	30
SE	544	19.7
SW	336	12.2
MW	417	15.1
Total	2765	100

Descriptive Statistics of Categorical Variables

I measured the study categorical variables, the IVs (physician home state, license state, field of license, age group, and graduation year group), and the DV (malpractice allegation group) to obtain the minimum, maximum, mean, standard deviation (stdv.), and mean variable rate of categorical values that occurred separately in each variable cases (please refer to Table 5 below for description). The largest physician type by degree in the sample was Osteopathic Phys Resident, at 40% mean rate of the sample (see Table 5 below).

The largest age group of practitioner was 46, at 57.5% mean rate of the sample. The state variables largest practitioners home State is the Midwest category at mean 50% of the sample. The largest practitioners' state of license is the Midwest category at 50% mean rate of the sample. The largest malpractice allegation group is others category at 0 % mean rate of the sample.

The mean variable rates were measured as the mean value divisible by the maximum value for each value then multiplied by 100. The total variable rates in this study ranged from 50%–100% with a mean variable rate of 60.0%. The results are summarized in Table 5 below.

Table **5**
Descriptive Statistics of Categorical Variables = Mean, Min, Max (N=2765)

Variable ID	N	Minimum	Maximum	Mean	Mean Variable Rate (%)	Std. Deviation
Graduation year group	2765	1950	2010	1982	98.6	12.45
Age Group of Practitioner	2765	30	80	46	57.5	11.59
Practitioners Field of License	2765	10	25	10	40	2.72
Practitioners Home State	2765	2	6	3	50	1.33
Practitioners State of License	2765	2	6	3	50	1.35
Malpractice Allegation Group	2765	0	1	0	0	.448
Total	2765					

Test of Statistical Assumptions

The assumption of normality and linearity of the data should be satisfied by conducting a correlation analysis. Normality assumption refers the extent to which observed variables in a sample are normally distributed. Linearity assumes that there is a direct relationship between two variables (Mertler & Vannatta, 2002, p.32). I conducted the normality test using the Kolmogorov–Smirnov and Shapiro–Wilk's tests as indicators.

Both tests indicated statistically significant results (p<.05) for all my variables (IVs and DV). Thus, the assumption of normality was not met (see Table 6a below).

Thus, I used the nonparametric alternative (i.e., the Spearman's correlation) to the Pearson correlation test.

The Spearman's correlation requires the assumptions of monotonicity is met. A scatter plot was used to verify the monotonicity of the data in the independent variables and dependent variable components. The data variables met the assumptions of monotonicity as categorically ordered variables. Therefore, the Spearman's correlation was applied to answer the research question.

Table 6a

Assumptions for Normality Test

Kolmogorov– Smirnov and Shapiro –Wilk	
Allegation Error Type	Sig.
Age Group	.000*
Graduation Year Group	.000*
Field of License	.000*
Home State	.000*
State of License	.000*

Notes. * p <.05

To confirm that a logistic regression analysis was the most appropriate method for analyzing the data, I assessed the assumptions of linearity of logit and multicollinearity. The independent variables and the dependent variable were evaluated for linearity of logit to check for interactions between them. A linear regression analysis indicated that assumption of multicollinearity were met, indicating that the variables were not highly collinear, with evidence showing the tolerance values are greater than 0.1, and all variance inflammation factor (VIF) values are below 10 (Mertler & Vannatta, 2002) (see

Table 7). In addition, there were no significant interaction effects (p >.05). The assumption requires that predictor variables not be highly correlated with each other to avoid linearly predicting one from the other with a substantial degree of accuracy because logistic regression is sensitive to high correlation among the independent variables (Mertler & Vannatta, 2002, p. 317). There was no mulicolinearity. Therefore, I proceeded with the analysis because a binary logistic regression analysis can be used to answer the study research question on the basis that all underlying assumptions for applying the statistical test were met.

Table **7**

Assumption Test (Linear Regression Multicollinearity): Low Collinearity Demonstrated by High Tolerance and Low VIF Values from the SPSS Software Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance (0-1) >1	VIF <10.
(Constant)	1.176	2.775		.424	.672		
Age Group of Practitioner	-.001	.001	-.022	-.569	.569	.250	3.999
Graduation year group	.000	.001	-.007	-.173	.862	.248	4.039
Field of License	.008	.003	.048	2.497	.013	.974	1.026

Home State	-.029	.013	-.087	-2.237	.025	.239	4.186
State of License	.022	.013	.067	1.720	.086	.239	4.186

Notes. Dependent Variable: Allegation Error Type

Inferential Analysis

Bivariate Analysis

Research Question1: What is the association between the selected physician characteristics described above and surgical errors?

H1: There is an association between physician home state and surgical errors.

H2: There is an association between physician state of license and surgical errors.

H3: There is an association between physician field of license and surgical errors.

H4: There is an association between physician age group and surgical errors.

H5: There is an association between physician medical school graduation year group and surgical errors.

The Spearman's rank correlation was appropriate for examining the relationship between physician home state and surgical errors, the relationship between physician state of license and surgical errors, the relationship between physician field of license and surgical errors, the relationship between physician age group and surgical errors, and the relationship between physician medical school graduation year group and surgical error. I included the independent variables of interest (i.e., physician home state, physician state of license, physician field of license, physician age group, and physician medical school graduation year group) along with the outcome variable of interest, surgical error.

Physician field of license was correlated with surgical errors ($r_s = -.051$, n= 2765, $p < 0.008$). Surgical errors were not correlated with physician home state, physician state of license, physician age group, and physician medical school graduation year group. The results are summarized in Table 8.

Table 8

Bivariate Statistics Correlations of Categorical Variables (N = 2765)

	Age Group of Practitioner	Graduation year group	Practitioners Field of License	Practitioners Home State	Practitioners State of License	Malpractice Allegation Group
Malpractice Allegation Group	-0.022	0.018	.051*	-0.015	-0.003	1

Notes. * *p* <.05.
+1= Total positive correlation
0 = No correlation
-1 = Total negative correlation

Multiple Binary Logistic Regression with Covariates and Surgical Errors to Predict Errors

H1: There is an association between physician home state and surgical errors.

H2: There is an association between physician state of license and surgical errors.

H3: There is an association between physician field of license and surgical errors.

H4: There is an association between physician age group and surgical errors.

H5: There is an association between physician medical school graduation year group and surgical errors.

A binary logistic regression analysis was appropriate for evaluating the association between the selected physician characteristics (i.e., physician home state, physician state of license, physician field of license, physician age group, and physician medical school graduation year group) and occurrence of surgical errors. I conducted a binary logistic regression analysis by using SPSS. To be able to use a binary logistic regression to analyze data, the dependent variable, surgical error, was coded as a dichotomous variable with two outcomes (surgery = 0; others = 1). The independent variables were all categorically coded (see Table 9 below).

Table 9

Case Processing Summary: Binary Logistic Regression with Covariates and Surgical Errors to Predict Errors (N=2765)

Unweighted Cases		N	Percent
Selected Cases	Included in Analysis	2765	100
	Missing Cases	0	0
	Total	2765	100
Unselected Cases		0	0
Total		2765	100

The output for logistic regression includes statistics for overall model fit, classification table, and summary of model variables. Results of the logistic regression model was statistically significant at □2 = 56.026, p = .000 (see Table 10), indicating there is a significant effect of the merged predictors on the dependent variable.

Table 10

Block 1: Method = Enter: Omnibus Tests of Model Coefficients

		Chisquare	df	Sig.
Step 1	Step	56.026	20	.000

	Block	56.026	20	.000
	Model	56.026	20	.000

The possible associated variables were physician home state, graduation year group, physician state of license, and field of license. The Hosmer–Lemeshow goodnessof-fit was not significant at .559 ($p > 0.05$), indicating the model is correctly specified

(see, Table 11 below). The p-value should be greater than the cut-off value (generally 0.05) to indicate that the model is a good fit.

Table 11

Hosmer–Lemeshow Test

Step	Chi-square	df	Sig.
1	6.798	8	.559

Additionally, the -2 log likelihood is 3207.396 and the Nagelkerke R squared is.029 (see Table 10a below). The Nagelkerke approximation was calculated in a manner constrained between 0 and 1(see Table 10b below). The larger the Cox and Snell estimate, the better the model fit is. The Cox and Snell estimate can be >1.

Table 12a.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square

1	3207.396	.020	.029

Notes. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Table 12b

Dependent Variable Encoding

Original Value	Internal Value
Surgery	0
Other	1

The important information from the classification table is the overall percentage of 72.3, which shows how well the model correctly classified the predicted observed cases (see Table 13 below).

Table 13

Classification Table

Observed	Predicted Malpractice Allegation Group Surgery		Percentage Correct others		
Malpractice Allegation Group	Surgery	0	766	0	Malpractice Allegation Group
	others	0	1999	100	
Overall Percentage					72.3

Notes. The cut-off value is .500.

The model result showed that some independent variables—graduation year group ($p = .363$), age group of practitioner ($p = .659$), and physician home state ($p= .273$)—were not significant. However, other independent variables, such as field of license ($p = .013$) and physician state of license ($p = .001$, .037, and .000), were found to be significant. The physician home state variable, though not significant, has significant p values in its two-coded categories, which may be considered in future studies: homestat region coded (1) ($p = .099$) and homestat region coded (3) ($p= .063$). The significant independent variables in the logistic regression analysis were found to contribute to the model. Only two of the predictor variables, including some of their categories of the five predictor variables, were statistically significant (i.e., physician state of license and field of license). The results are shown in Table 12 below.

The logistic coefficient for each independent variable in the error model is the expected amount of change in the logit for each one unit change in it. The analysis described the Wald static (Z test), B (logic coefficient), Exp (B) (odd's ratio), Cl for Exp (B) and P-value. Predictors in the Exp (B) logit model that increase or have an effect on logit will display values > 1.0, and predictors that decrease or have no effect will display < 1.0 values (Newsom, 2015). The nearer the logistics coefficient B is to zero, the less influence it will have in predicting the logit, and the Wald Chi-square shows the test of significance of an individual predictor distributed with one degree of freedom (Newsom, 2015).

Physician field of license significantly affects surgical errors ($B = .044$, Wald = 6.193, $p = .013$, Exp (B) = 1.045, 95% CI (1.009, 1.081), for every increase of physician field of license. The independent variable, physician field of license, in the logistic regression analysis was found to contribute to the model. Additionally, the positive logistic coefficient (B value) for physician field of license (see Table 12 below) signifies that increased field of license was associated with increase in surgical error identification. The physician state of license variable was significantly associated with surgical error (Wald =19.888*,* p = .001). First, physician state of license region 1 significantly affects surgical errors (B = -.557, Wald = 4.347, p = .037, Exp (B) = .573, 95% CI (.339, .967)) for every increase of physician state of license. Second, physician work by state of license region 4 significantly affects surgical errors (B = -.788, Wald = 14.308, p = .000, Exp (B) = .455, 95% CI (.302, .684)) for every increase of physician work by state of license.

The negative logistic coefficient (B value) for any of the variables (see Table 12 below) indicated that an increase in that variable was associated with decrease in surgical error identification. However, for every unit increase in that variable, there was a logic coefficient (B) reduction in surgical error identification. Based on the result of the logistic regression model analysis, four statistical significant associations were found in two variables. The null hypothesis was rejected and can be concluded that two independent variables—physician state of license and physician field of license—significantly affect surgical errors. In addition, the physician home state variable was approaching significance, which may serve as an additional evidence to support null rejection.

Table 14
Variables Included in Calculation

	B Log. (> .0)	S.E.	Wald	df	Sig.	Exp(B) 95% C.I.for coefficient (Z test) Odd's ratio(>1.0)	EXP(B) Lower	Upper
practage			3.264 .387	5	.659			
			.797	1				
	-.573	.920			.534	.564	.093	3.425
practage(1)			.737	1				
	-.813	.910			.372	.444	.075	2.642
practage(2)				1				
			.720					
	-.773	.901			.391	.462	.079	2.696
practage(3)				1				
	-.755	.890			.396	.470	.082	2.688
practage(4)								

	practage(5)	-.615	.877	.492	1	.483	.540	.097	3.017
	grad			6.569	6	.363			
Step 1	grad(1)	-.551	.828	.443	1	.506	.576	.114	2.922
	grad(2)	-.718	.637	1.269	1	.260	.488	.140	1.701
	grad(3)	-.752	.608	1.528	1	.216	.471	.143	1.553
	grad(4)	-.428	.594	.519	1	.471	.652	.204	2.087
	grad(5)	-.644	.589	1.197	1	.274	.525	.165	1.665
	grad(6)	-.671	.592	1.284	1	.257	.511	.160	1.631

licnfeld	.044	.018	6.193	1	.013*	1.045	1.009	1.081
homestat_newregioncodes			5.143	4	.273			
homestat_newregioncod es(1)	.440	.267	2.719	1	.099	1.552	.920	2.618
homestat_newregioncod es(2)	.216	.264	.668	1	.414	1.241	.739	2.084
homestat_newregioncod es(3)	.430	.232	3.447	1	.063	1.538	.976	2.422
homestat_newregioncod es(4)	.140	.227	.382	1	.536	1.151	.737	1.796
ilnstat_newregioncode			19.888	4	.001*			
ilnstat_newregioncode(1)	-.557	.267	4.347	1	.037*	.573	.339	.967
ilnstat_newregioncode(2)	-.182	.278	.427	1	.514	.834	.484	1.438
ilnstat_newregioncode(3)	-.247	.254	.945	1	.331	.781	.475	1.285
ilnstat_newregioncode(4)	-.788	.208	14.308	1	.000*	.455	.302	.684
Constant	1.921	1.101	3.047	1	.081	6.828		

Notes. * p <.05. a. Variable(s) entered on step 1: practage, grad, licnfeld, homestat_newregioncodes, and ilnstat_newregioncode.

Effect Size, Post-Hoc Power Analysis, and Probability

A binary regression analysis is measured by a pseudo R^2 value (Nagelkerke R^2). A binary regression analysis can be interpreted in the same way as R^2 value in a multiple regression analysis and can be used to estimate Cohen's f^2, a measure of effect size.

The Cohen's f^2 can be calculated as a R^2 divided by one minus R^2 (see Figure 1). The Nagelkerke R^2 value in this study was 0.29. The Cohen's f^2 is therefore 0.408, which signifies a medium effect size. However, the G*Power computation was used to compute the post-hoc analysis to calculate achieved power given the alpha, the effect size, and the sample size. Computation applied an alpha level set at 0.05, Cohen's f^2 of 0.408, the number of predictors (5), and the sample size of 2,765 (the actual number of cases used for a binary logistic regression). The power analysis was computed as post-hoc, using the f-test, and a linear multiple regression statistical analysis: fixed model, R^2 deviation from zero. The post-hoc analysis showed that a statistical power of 1.0000000 was attained (see Figures 8 and 9 in appendix).

Figure 1

The formula to calculate is:

$$\text{Cohen's } f^2 = \frac{R^2}{1 - R^2}$$

Probability: the table gives the parameter estimate for a logistic regression analysis, the equation: Log (odd) = A +B1*+ (B) +CI*(C). To compute probability, based on I, the relationship that odds =p/ (1-p) when p is the probability. Solving for p, we get: P = odds / (1+odds).

The statistically significant predictor association revealed by a logic regression analysis showed that the probability of association of errors with the significant independent variables is an indication of the errors events that are likely to be identified by these physician characteristics (See Table 15a and Figure 7 in Appendix).

Table 15a

Probability Rate

Sig. Variables odd ratios	Probability
Physician State of License	(P =.001)
Licnregion(1)	0.364 (p = .037)
Licnregion(4)	0.312 (p = .000)
Field Of License	0.511 (p = .013)
Physician Home State	0.608 (p = .099)
(at the threshold)	0.605 (p = .063)

I also conducted further post-hoc tests: the Bonferroni-corrected p-values for pairwise comparisons of my significant correlation to avoid making a Type I error. The Bonferroni-adjusted p-values (BA) is a simple way to make the significant p value more conservative to avoid making a Type I error, also known as family-wise error, of rejecting the null hypothesis when it should be accepted. The theory is that if you analyze several independent variables, the more you analyze, the more likely you will find significance by chance alone. The BA formula is .05/N. Therefore, I divided the original alpha level of .05 by 5 to revise my significance level to p < or = .01.

At p < or = to .01, the BA will determine how many predictors are now significant compared to if a predictor was significant at p < or = to.05. The result of all my adjusted p value and correlation indicated the physician field of practice was significant at p = .008 when alpha was .05, and also p = 0.0016 after the BA at alpha .01, showing an unlikely possibility of Type I error for that variable outcome (see Table 13b for results).

Table 15b

Bonferroni-adjusted p-values (N=2765)

Bonferronivalues justed p- (BA)		Age Group of Practitioner	Graduation year group	Practitioners Field of License	Practitioners Home State	Practitioners State of License
Malpractice Allegation Group	Correlation Coefficient	-0.022	0.018	.051**	-0.02	-0.003
	BA	-0.0044	0.0036	0.0102	-0.004	-0.0006
	Sig.(2 tailed)	0.245	0.349	0.008	0.285	0.86
	BA	0.049	0.0698	0.0016	0.057	0.172
	N	2765	2765	2765	2765	2765

Summary and Transition

The purpose of this study was to quantitatively explore the association between selected physician characteristics (i.e., physician's work state, home state, state of license, field of license, age group, and medical school graduation year group) and surgical errors in U.S. hospitals. I conducted a secondary analysis of archived data using the National Practitioner Data Bank. I sampled 2,765 valid cases reported to the National Practitioner Data Bank in 2015 for my analysis. I used Spearman's rank correlation analysis to determine if there was a significant association between physician characteristics and occurrence of surgical error. I conducted binary logistic regression analysis to identify the best predictors that are significantly associated and have an influence on surgical error identification. Spearman Rank correlation analysis showed that physician field of license was associated with surgical errors ($r_s = -.051$, $n = 2765$, $p < 0.008$) even after a Bonferoni adjustment for significance. The results of the multiple binary logistic regression analysis revealed that physicians' state of license and physicians' field of license significantly affected surgical errors. Physicians' home region variables in the categories, homestat_region coded (1) at ($p = .099$) and homestat region coded (3) at ($p = .063$), were also near the significance threshold.

Section 4 will present discussion and interpretation of the study results. It also discusses the relation of the study findings to the published literature and knowledge base. It concludes with a discussion of the study, limitations and generalizability of the results, and implications for positive social change.

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

The purpose of this study was to quantitatively explore the association between selected physician characteristics (physicians' work state, home state, state of license, field of license, age group, and medical school graduation year group) and surgical errors in U.S. hospitals. The reason for conducting the study was because not enough is known about the relationship between physician characteristics and surgical errors. Additionally, the literature review confirmed a high rate of surgical errors that threatens patients' safety in health care settings.

I conducted a quantitative correlational study to measure the association between the independent and dependent variables. The dependent variable was surgical error classified by malpractice allegation type.

A quantitative correlational study was most appropriate for measuring the association between the independent and dependent variables. The data were collected from the National Practitioner Data Bank (NPDB) administered by the Health Resources and Services Administration (HRSA) of the U.S. Department of Health and Human Services (USDHHS.HRSA, 2015).

After data sampling and management, I used a logistic regression analysis to assess the association between the final selected physician characteristics (physicians' home state, state of license, field of license, age group, and medical school graduation year group) and occurrence of surgical errors. Results of the analysis indicated that there were no statistically significant associations between the dependent variable and three of the independent variables: graduation year group (p = .363), age group of practitioner (p = .659), and physician home state (p = .273). However, there were statistically significant relationships between the dependent variable and two independent variables: field of license (p = .013) and state of license (p = .001, .037, and .000). Two of the predictor variables, were statistically significant (i.e., physician state of license, and field of license).

Interpretation of the Findings

Analysis of the results of this study offered insight that confirmed and expanded the findings from the literature**.** The primary research question for this study was this: What is the association between physician characteristics and surgical errors? In the study, the model results showed the independent variables graduation year group (p = .363), age group of practitioner (p = .659), and physician home state (p = .273) had no statistically significant relationship with the dependent variable. However, the independent variables physician field of license (p = .013) and physician state of license (p = .001, .037, and .000) were found to be significant. These findings support previous studies.

D'Addessi, Bongiovanni, Volpe, Pinto, and Bassi (2009) conducted a review that provided background on human factors in surgery as a field of study in safety improvement, and further discussed its application to the operating theater and surgical team communication. D'Addessi et al. identified that the causes of surgical errors in medical care are commonly thought of as the consequence of lack of skill or ability and are the result of careless actions. D'Addessi et al. explained that the identification and study of human factors is important for safety because they can be the cause of severe human errors due to physical behavior and sociocognitive decision-making. D'Addessi et al. revealed that the areas of interest for human factors in practitioners include training, communication, task analysis, work allocation, job descriptions and functions, knowledge, skills, and abilities affecting surgical errors. D'Addessi et al.'s (2009) findings aligned with those in the current study indicating that field of license and physician state of license significantly affected surgical errors. This could be the result of differences in the training received or types of work environment. Also, the report gave direction to the study's conceptual models of intrapersonal factors and HBM connected to physician behavior to surgical error.

Alkhenizan and Shaw (2011) performed a meta-analysis to evaluate the impact of accreditation programs on the quality of health care services in hospitals. Alkhenizan and Shaw evaluated 26 studies and found that general accreditation programs have significant, positive impact on improving patient safety outcomes. Alkhenizan and Shaw (2011) saw that accreditation programs improve the process of care delivered by health care practitioners. The evidence in Alkhenizan and Shaw's (2011) study conforms to the findings in the current study that field of license and physician state of license significantly affected surgical errors.

The types of accreditation differ from state to state and field of practice. A statement released by the National Center for Complementary and Integrative Health (NCCIH, 2016) explained that "the credentials required for complementary health practitioners vary tremendously from state to state and from discipline to discipline" (para. 3). This issue may affect how errors are described and defined, the regulation of what and how they are reported, including polices and penalties concerning errors committed by practitioners. In addition, medical errors researchers believe that a uniform system for reporting errors (a standardized data collection and reporting processes) is needed in the United States, as well as agreement on how to define medical errors (Makary & Daniel, 2016, p. 2). The ecological model (EM) and the health behavior model (HBM) were the two conceptual models used in the study to help understand the findings. The EM model highlights the links among multiple factors that affect health and focuses on individual and population determinants of health and intervention. The EM model emphasizes the social and physical environments of public health problems such as causes of diseases and injuries and responses to them.

The EM model can be applied to the problem of surgical errors and understanding their root causes. Errors are probably the result of human factors as well as intrapersonal and environmental factors. The EM health status and behavior are the outcomes of interest and are determined by five factors: public policy, community, institutional, interpersonal, and intrapersonal (Healthy Campus 2020, 2016). The EM factor I used in this study was the intrapersonal factor, which comprises individual characteristics such as demography, skills, attitudes, behavior, self-concept, and developmental history, which relates to the physician characteristics (independent variables) used to predict surgical error (dependent variable).

The specific aspects of EM that relate to the physician characteristics (independent variables) are the intrapersonal factors of the model that are centered on perceptions and risk factors (e.g., how field of license and physician state of license motivate, influence, or affect how the individuals [physicians] behave and increase their probability of committing an error). The EM framework is illustrated in Figure 4.

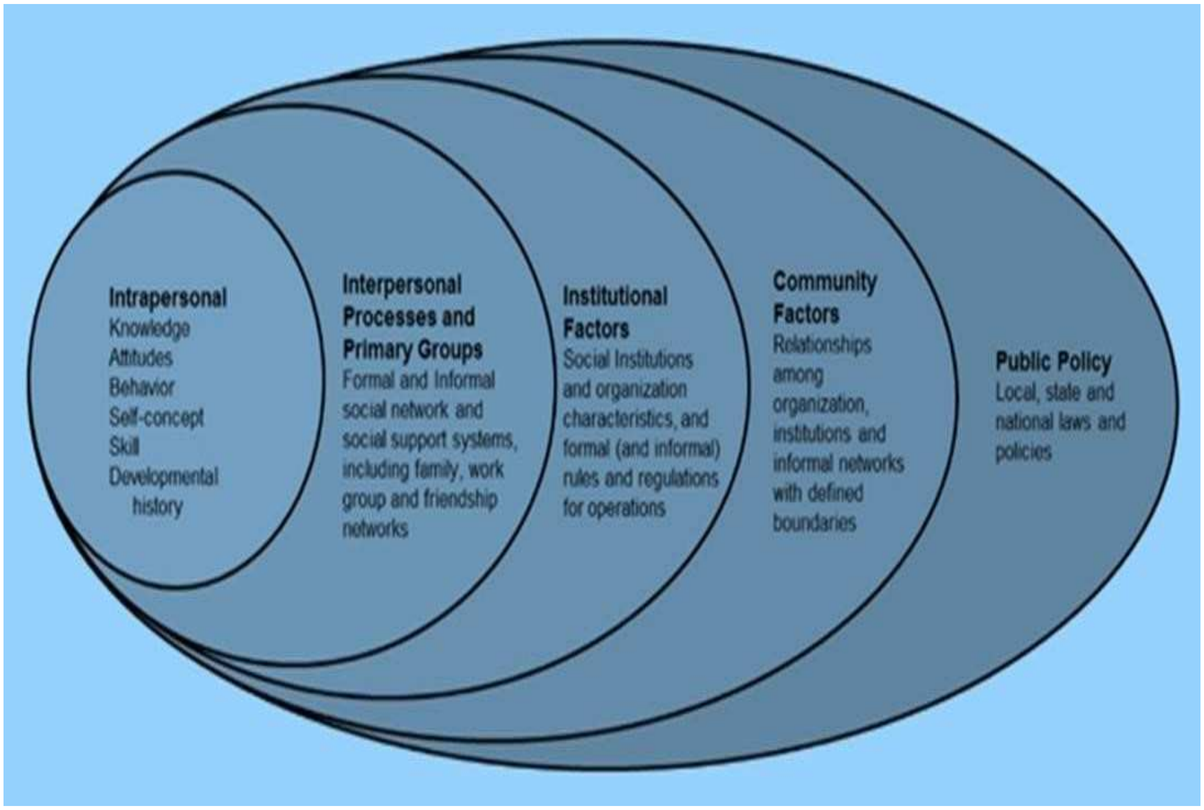

Figure 4. EM conceptual framework (reprinted from Healthy Campus 2020, 2016).

Medical errors, including surgical errors, are underreported or "never reported voluntarily or captured through other mechanisms" (Wolf & Hughes, 2008, p. 2). Although this study did not focus on surgical errors per se, it is instructive to use the health belief model (HBM) to understand the role of personal characteristics described in the ecological model. The HBM theory helps to understand how individuals take a health-related action through their perceived susceptibility (risky behavior) and severity (knowledge) of a health problem. Through the HBM constructs, the cues to action such as readiness and taking action to report surgical errors may be realized through physicians adopting a behavior change to surgical report errors. The HBM is illustrated in Figure 5

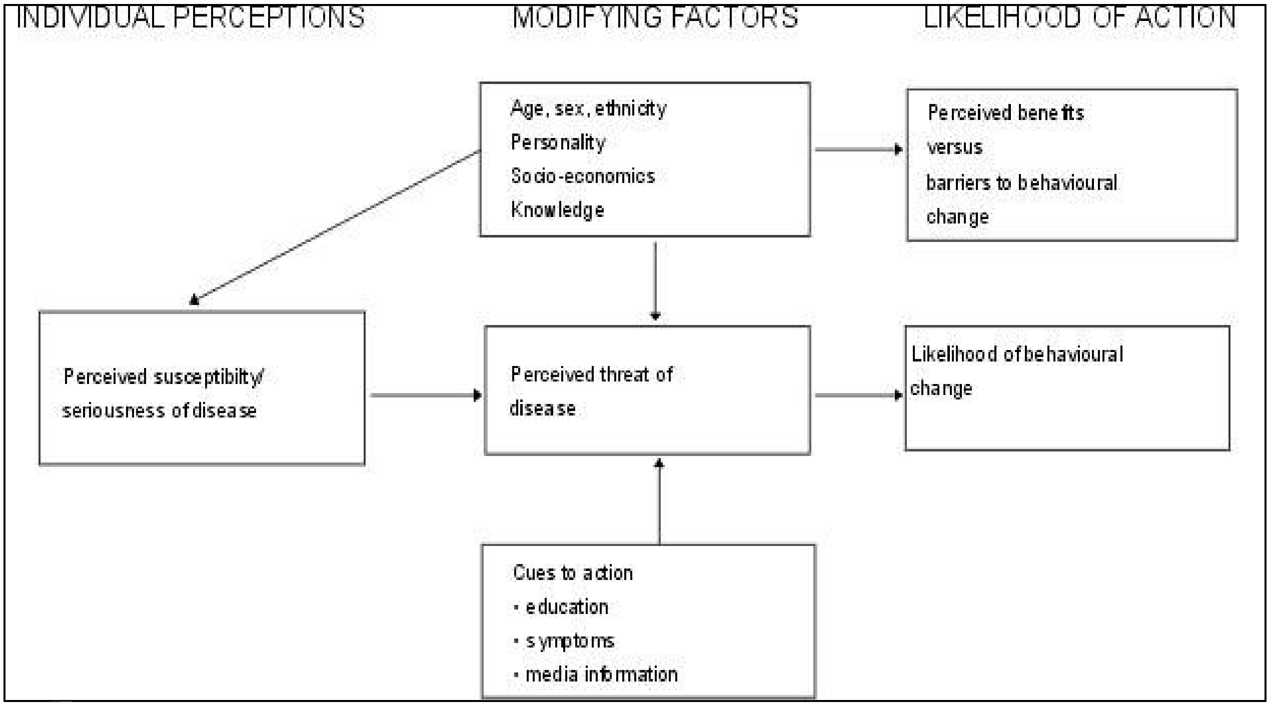

Figure 5. HBM conceptual frame work (reprinted from University of Twente, 2012).

Conceptually, combining EM and HBM might provide a clearer understanding of the factors responsible for surgical errors and their under reporting (see Figure 6.

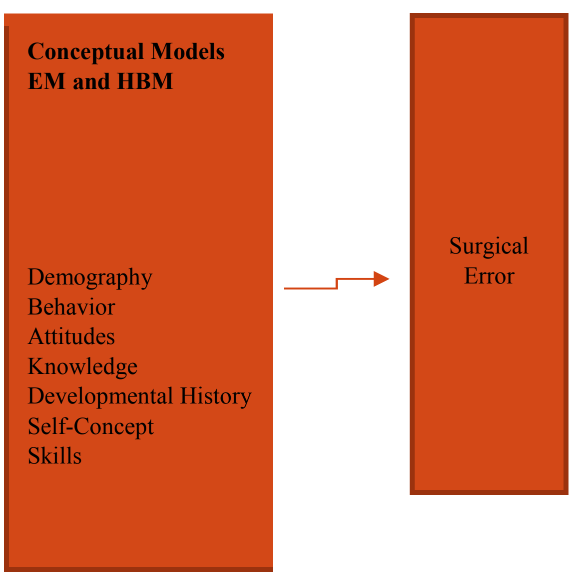

Figure 6. Conceptual Framework Sketch

Limitations of the Study

Threats to internal validity are research procedures and other factors that can obstruct the researcher's ability to make correct inferences from observed populations in a study (Creswell, 2009). There are diverse internal threats to validity. Because this study involved a secondary analysis of archived data, I had no control over the original data collection. The NPDB database used for this study contains a large archived public use data set designed for research purposes. The data set contains de-identified information on specific variables of Adverse Action Reports and Medical Malpractice Payment Reports on licensed practitioners and other health care workers. Additionally, data from this source are collected through convenient sampling and generated through voluntary querying and reporting.

Threats to external validity occur when a researcher makes incorrect generalizations from the sample data to other populations or situations (Creswell, 2009). The threat to external validity in my study was that the data might be neither valid nor reliable. I was confident that my external and future validity were very low. However, the ability to generalize results to people/populations that were not included in the study (University of South Alabama, 2016) might be limited.

An inappropriate sampling method might affect study results by causing a bias in the data analysis therefore, I offered edits to enhance clarity and concision. In addition, the data were reported through voluntary means, which might limit my results. Another issue was the possibility of the data not answering the research questions because the data were collected for some other reason, even though the data set contained elements needed for and related to the current study.

Recommendations

Peer-reviewed studies that addressed the association between physician characteristics and surgical errors are minimal. In future studies, it would be helpful to determine whether physician characteristics significantly affect surgical errors while controlling for gender, age, and ethnicity.

The present study showed variations between the age groups on physician error: Those ages 20 through 39 had a low rate of error occurrences, those ages 40 through 59 had a very high rate of error occurrences, and those age 70 through 89 had a lower rate (see Table 16 cross tab results).

Table 16

Crosstab and Chi-Square Test Analysis for Selected Independent and Dependent Variables

Age Group of Practitioner	Count	Total(N=2765)
Ages 30 - 39	127	
Ages 40 - 49	228	
Ages 50 - 59	206	
Ages 60 - 69	165	
Ages 70 - 79	38	
Ages 80 - 89	2	
		266 of 2765
Graduation year group		
1950 - 1959	6	
1960 - 1969	71	
1970 -1979	165	

1980 - 1989	223	
1990 - 1999	222	
2000 - 2009	113	
2010 - 2019	4	
		766 of 2765
Practitioners Field of License		
Allopathic Physician (MD)	716	
Physician Resident (MD)	2	
Osteopathic Physician (DO)	44	
Osteopathic Physician Resident (DO)	1	
		766 of 2765
Practitioners Home State		
W	138	
NE	250	
SE	149	
SW	82	
MW	147	
		766 of 2765
Practitioners Field of License		
W	191	
NE	210	
SE	126	
SW	133	
MW	106	
		766 of 2765

The result indicated that the younger the practitioner, the higher the likelihood of committing an error. Reflecting on this result, future researchers may examine surgical error controlling for age as one of the influencers of error-committing behaviors, which may provide further insight in predicting errors.

I used a cross-sectional methodology to examine the impact of physician characteristics on surgical errors. For future studies, a longitudinal research design should be used to examine the impact of physician characteristics on surgical errors, controlling for gender, age, and ethnicity. Longitudinal studies can be used to detect and establish the orders of events in the characteristics of the observed population at both the group and the individual level (Institute for Work & Health, 2015).

Researchers should conduct a qualitative study that explores the experiences of practicing physicians, which may reveal their perceptions as to why surgical errors occur. A qualitative study can be used to gain an understanding of opinions, perceptions, and motivations regarding surgical error rates and reporting issues.

Researchers should also examine the association between physicians' field of license and physicians' state of license and surgical errors at different hospitals and clinics in the United States.

Implications for Professional Practice and Social Change

Professional Practice

The findings of the study have several implications for professional practice. More clinical-based research is needed to understand the rates and causes of surgical errors. The results may be used to discover what factors affect surgical errors. The results can be used as a screening tool when selecting potential physicians. This study can add to the body of knowledge on the impact of physician characteristics on surgical errors.

The study can be beneficial to hospitals as it provides information for who might be a good fit for the organization. Enhancing physician skills can enable health care leaders to improve overall training.

Healthcare leaders can use the results for case analysis of actual situations. The results regarding the association between physician characteristics and surgical errors may be contrasted with actual surgical errors. The present study may provide a basis for development of programs.

Theoretical Implications

The present study was guided by the ecological model (EM), also called socialecological model (SCM). EM is a model of health care studies that emphasizes the linkages and relationships among multiple factors or determinants affecting health and is focused on both population-level and individual-level determinants of health and interventions (Miller, 2013). Health (surgical error) under this model may be determined by influences at multiple levels that include public policy, community, institutional, interpersonal, and intrapersonal factors (American College Health Association, 2015, para.1).

I employed the health care EM to understand the etiological factors behind surgical errors because it provides a thorough view of the complex connections between health, treatment, outcome, and health care structure. Moreover, health care ecology recognizes environmental factors and influences, which interact with and affect individual behavior. These factors include physical setting, the human characteristics of the people and surrounding public, and organizational and social environment (American College Health Association, 2015). In addition, health care practitioners, educators, patient safety leaders, and researchers can recognize the value of human factors in addressing patient safety (Miller, 2013).

Methodological Implications

Researchers using correlational studies have the capability to explore the associations between variables and possibly identify predictors for preventing errors in the future. Hospital safety and clinical experts can collect data or use their existing data to conduct further studies that would shed light on the problem.

Positive Social Change

My study helped to fill the gap in understanding provider characteristics that may be associated with surgical error incidence. My study may help advance patient safety practice by identifying physician characteristics that may help predict the occurrence of surgical errors. In addition, this study may assist in understanding practitioners' behavior patterns and other factors that may assist in preventing future surgical errors and protecting patients from adverse outcomes due to errors. This study may help practitioners create a change in work culture toward a collaborative work leadership to reduce surgical errors and its damaging effects on patients and health care providers.

Conclusion

The results of this study revealed that the physicians' field of license and state of license are statistically associated with surgical errors. Physicians' field of license and physician's state of license may greatly affect surgical error rates, threatening patient safety in surgical or operating rooms in hospitals and clinics. Physician characteristics may be important factors in predicting which clinicians are likely to commit surgical errors; however, more research is needed to confirm this. Health care leaders, health providers, and researchers should monitor closely physicians' skills, expertise, training conditions, license, and work capabilities, which may affect their proper adherence to policies and processes in their practicing work environment. Health care organizations should continue to monitor clinician characteristics and behaviors such as team work and communication skills processes, and systems for measuring and reporting surgical error rates should be further improved and researched to protect patients and avoid adverse surgical outcomes.

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Appendix A: Data Analysis Tables

Table 1. *Independent, Dependent Variables, and Level of Measurement*

Variable Names	Types	Level of Measurement
Physicians work state	Independent	Nominal (continuous with Discrete Categorical)
Physicians home state	Independent	Nominal (continuous with Discrete Categorical)
Physicians state of license	Independent	Nominal (continuous with Discrete Categorical)
Field of license	independent	Scale (continuous with Discrete Categorical)
Age group	Independent	Scale (continuous)
Graduation year group	Independent	Scale (continuous)

All surgical errors	Dependent	Nominal

Table 2. *Data Dictionary*

	Data Dictionary		
Variables (Code Description)	Variables Defined	Record Type	Code Id
Physicians work state	50 U.S. states	String will be change to numeric	workstat
Physicians home state	50 U.S. states	string will be change to numeric	homestat
Physicians state of license	50 U.S. states	string will be change to numeric	licnstat
Field of license	Allopathic Physician (MD); Physician Resident (MD); Osteopathic Physician (DO); Osteopathic Physician; Resident (DO); Dentist; Dental Resident; Nurse Practitioner; Doctor of Nursing practice	numeric	licnfeld
Age group of practitioner	19 through 99	numeric	practage
Graduation year group	1990 to 1989	numeric	grad
All surgical errors	Surgery-Related; DiagnosisRelated; Anesthesia-Related; Medication-Related; IV & Blood Products-Related; Obstetrics-Related; Treatment-Related;	numeric	alegnnatr

	Monitoring-Related; Equipment/Product-Related; Other Miscellaneous; Behavioral Health-Related		

Table 3. *Overall Data Analysis Plan Matrix*

RQ : Null hypothesis	**Dependent Variable**	**Independent Variables**	**Statistic**
1a. H0: There is no association between physician work state and occurrence of surgical errors. 2a. H0: There is no association between physician home state and occurrence of surgical errors 3a. H0: There is no association between physician work by state of license and occurrence of surgical errors. 4a. H0: There is no association between physician field (specialty) of license and occurrence of surgical errors. 5a. H0: There is no association between physician age and occurrence of surgical errors.	Binary outcome variables: presence of Surgical errors (reflect outcome)	Physician work state Physicians home state Physicians work by state of license Field of license Age group Graduation year group	Descriptive statistics Bivariate: Chi Square - correlate-bivariate, cross tabulation, Pearson's correlation. Multivariate: Multivariate logistic regression (Multiple regression). Binary outcome variables: presence of Surgical errors (surgical/ Other errors) (reflect outcome) Regression steps to include: Predictor variables

6a. H0: There is no association between physician graduation year and occurrence of surgical errors.			

A. Descriptive Analysis

Descriptive statistics will report average age, total numbers, percentage distribution of cases, etc.

Objective: 1. Procedures: Frequencies (measures of central tendency), Percentages

Table 4. Description of Surgical Error by Physician Characteristics and, U.S. Physicians, 2015. (N = x)

Data Table				
Name	Type	Decimals	Measurable Unit	Value Label Id
Physicians Work State	string	0	Percentage (%)	Northeast Southeast Midwest Southwest West
Physicians Home State	string	0	Percentage (%)	Northeast Southeast

				Midwest Southwest West
Physicians State Of License	string	0	Percentage (%)	Northeast Southeast Midwest Southwest West
Field Of License	numeric	0	Percentage (%)	10 Allopathic Physician (MD) 15 Physician Resident (MD) 20 Osteopathic Physician (DO) 25 Osteopathic Physician Resident (DO)
Age Group Of Physicians	numeric	0	Years (yrs)	30 Ages 30 through 39 40 Ages 40 through 49 50 Ages 50 through 59 60 Ages 60 through 69 70 Ages 70 through 79 80 Ages 80 through 89 90 Ages 90 through 99
Physician Graduation Year	numeric	0	Years (yrs)	1900 1900 through 1909 1910 1910 through 1919 1920 1920 through 1929 1930 1930 through 1939 1940 1940 through 1949 1950 1950 through 1959 1960 1960 through 1969 1970 1970 through 1979 1980 1980 through 1989

All surgical errors(recoded as surgical error)	numeric	0	Percentage (%)	Surgical error present 20 Surgery Related Other errors = 1 Diagnosis Related 10 Anesthesia Related 30 Medication Related 40 IV & Blood Products Related 50 Obstetrics Related 60 Treatment Related
				70 Monitoring Related 80 Equipment/Product Related 90 Other Miscellaneous 100 Behavioral Health Related

B. Inferential Statistics

Mock Table 5. Logistic Regression of physician's work state, home state, state of license, field of license, age group, and graduation year group (Physician Characteristic) in predicting surgical errors, U.S. physicians 2015.

Predictors	Surgical errors					
	Bivariate: Chi Square - correlate-bivariate: Odds Ratios Of Having A surgical error Or not			*Multivariate logistic Regression:* model predictability for surgical errors		
	Odds ratio	Confidence interval	p-value	Beta weight	R^2-value	p-value
Physicians Work State						
Surgical error present (yes) Other errors (no)						
Physicians Home State						

Surgical error present Other errors						
Physicians State Of License						
Surgical error present Other errors						
Field Of License						
Surgical error present Other errors						
Age Group Of Physicians						
Surgical error present Other errors						
Physician Graduation Year						
Surgical error present Other errors						
Surgical Errors						
Surgical error present Other errors						

Model Chi-square *(p-value)*		
Model R^2 *(p-value)*		

Objective: 2. Procedures: Bivariate: Chi Square - correlate-bivariate, cross tabulation, Pearson's correlation.

Objective: 3. Multivariate: Multivariate logistic regression using SPSS Statistics: Procedures: (dichotomous dependent variable: continuous with discrete categorical independent variable).

Chi-Square Test Analysis for Selected Independent and Dependent Variables Table i

Chi-Square(X^2) Tests

Surgical error(DV) * Independent Variables(IV)			
Pearson Chi-Square	Value	Df	Asymp. Sig. (2Sided)
Age Group Of Practitioner	5.471	5	.361
Graduation year group	6.868	6	.333
Practitioners Field of License	8.574	3	.036
Homeregion24	19.045	4	.001
Licnregion24	34.346	4	.000

$P < 0.05$

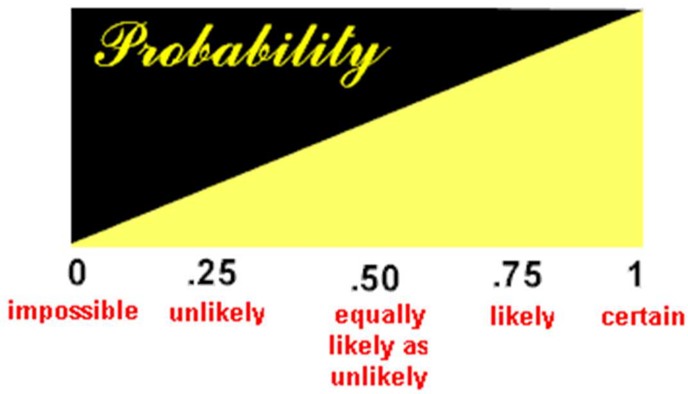

Figure 7. Probability Table

TABLE 2	Differences between Groups, Effect Size measured by Glass's D[a]		
Relative Size	Effect Size	Percentile	% of Nonoverlap
	0	50	0
Small	0.2	58	15
Medium	0.5	69	33
Large	0.8	79	47
	1.0	84	55
	1.5	93	71
	2.0	97	81

Figure C. Effect Size Ranges (Sullivan & Feinn, 2012).

TABLE 1	a Common Effect Size Indices		
Index	Description[b]	Effect Size	Comments
Between groups			
Cohen's d[a]	d 5 M_1 2 M_2 / s M_1 2 M_2 is the difference between the group means (M); s is the standard deviation of either group	Small 0.2 Medium 0.5 Large 0.8 Very large 1.3	Can be used at planning stage to find the sample size required for sufficient power for your study
Odds ratio (OR)	Group 1 odds of outcome ________ Group 2 odds of outcome If OR 5 1, the odds of outcome are equally likely in both groups	Small 1.5 Medium 2 Large 3	For binary outcome variables Compares odds of outcome occurring from one intervention vs another
Relative risk or risk ratio (RR)	Ratio of probability of outcome in group 1 vs group 2; If RR 5 1, the outcome is equally probable in both groups	Small 2 Medium 3 Large 4	Compares probabilities of outcome occurring from one intervention to another
Measures of association			
Pearson's r correlation	Range, 21 to 1	Small 60.2 Medium 60.5 Large 6 0.8	Measures the degree of linear relationship between two quantitative variables

r^2 coefficient of determination	Range, 0 to 1; Usually expressed as percent	Small 0.04 Medium 0.25 Large 0.64	Proportion of variance in one variable explained by the other

Figure 9. Effect Size Descriptions (Sullivan & Feinn, 2012).