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# The Relationship Between Hospitals' Electronic Health Records Maturity and Excess Readmission Ratio

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This is to certify that the doctoral study by

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has been found to be complete and satisfactory in all respects,
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Abstract

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MS, Walden University, 2015

BS, Fairleigh Dickinson University, 1992

BS, Montclair State University, 1990

Doctoral Study Submitted in Partial Fulfillment

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Abstract

Since the Health Information Technology for Economic and Clinical Health Act was enacted in 2009, a majority of U.S. hospitals have adopted electronic health records (EHR) to improve quality of care. However, variations exist in the technology's capability and maturity, making it difficult for researchers to analyze the full impact. The purpose of this quantitative study was to explore the relationship between hospitals' EHR maturity and the quality measure of excess readmissions, as well as the relationship between hospital characteristics, specifically, hospital location and the number of licensed beds in Medicare hospitals (*N* = 1,006). Both the chi-square statistical test and logistic regression models were used to analyze whether EHR maturity has an impact on excess readmissions. Rogers's diffusion of innovation provided the theoretical framework. A retrospective data analysis for FY 2017 was conducted using EHR adoption analytics from the Healthcare Information and Management Systems Society and excess readmission ratio (ERR) data from the Centers for Medicare and Medicaid Services' Hospital Readmissions Reduction Program. Analyses indicated no significant association between EHR maturity and ERR for either coronary artery bypass grafts or total hip or total knee arthroplasty (THA/TKA). However, there was a significant relationship between hospitals' EHR maturity, location, and number of licensed beds. In addition, EHR maturity and hospitals' location were significant predictors of elective primary THA/TKA ERR. The results of this study may lead to positive social change by informing hospital administrators on the impact of investments in mature EHR technology to reduce excess readmissions and improve quality of care.

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## Dedication

I dedicate this doctoral study to the memory of my beloved grandmother Hildred Frazer, who even though she only had a fourth-grade education, instilled in me the love of learning. I am grateful for her love and contribution. I also dedicate this study to my children, Darren and Jessica Saint-Ulysse, who supported me and encouraged me to achieve this goal.

## Acknowledgments

I would like to acknowledge my chair, Dr. Robin Carlson, and my committee member, Dr. Matt Frederiksen-England, for all their support, positive feedback, and encouragement during this very long process. I want to thank my aunt Sandra London for her prayers.

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# Section 1: Foundation of the Study and Literature Review

In this study, I examined the relationship between hospitals' electronic health record (EHR) maturity, as measured by the stage in Healthcare Information Systems Management's (HIMSS) Electronic Medical Record Adoption Model (EMRAM), and excess readmissions, as measured by the excess readmission ratio (ERR), for the Hospital Readmissions Reduction Program (HRRP) procedure-specific conditions. These conditions included coronary artery bypass graft (CABG) and elective primary total hip or total knee arthroplasty (THA/TKA). Maturity is the optimization of a technology (Tarhan et al., 2020). A mature EHR suggests capabilities that support a fully electronic, paperless environment and integrated electronic communication with other healthcare systems (Gomes & Romão, 2018). Excess readmissions are defined based on Medicare's calculations of expected readmissions compared to other similar hospitals' averages (Centers for Medicare and Medicaid Services [CMS], n.d.-b). Additionally, I explored the relationship between hospitals' characteristics, such as hospitals' location (micropolitan or metropolitan) and the number of licensed beds and ERR.

The results of this research could inform hospital administrators about investment in technology that supports the diffusion and spread of innovation and improve quality care throughout Medicare-participating hospitals in the United States. Furthermore, although the study population was limited to Medicare hospitals with the procedure-specific conditions of the HRRP, the results of this quantitative study could be applicable to other population groups and conditions. In 2011, there were 3.3 million hospital readmissions, which cost the U.S. economy an estimated $41.3 billion (NEJM Catalyst, 2018). Reducing excess readmissions can improve quality care and strengthen patients' trust and confidence in the healthcare system. These benefits align with the triple aim of healthcare reform in the United States of better-quality care, decreased cost, and improved patient experiences (Sheikh et al., 2015).

In this section, I provide the background of the problem, state the research problem and study purpose, and discuss the study's relevance for healthcare administrators. In addition, the section contains the research questions (RQs) and hypotheses, theoretical framework, and the nature of the study, followed by the literature review, which will include discussion of the study variables and the gap in the literature that I addressed. Definitions and the assumptions, scope and delimitations, limitations, and significance are also included in this section.

## Background

U.S. lawmakers enacted the Health Information Technology for Economic and Clinical Health (HITECH) Act in 2009 to incentivize healthcare providers to adopt health information technology (HIT) in their practices (Atasoy et al., 2019). The legislation, which was part of the American Recovery and Reinvestment Act, provided an estimated $30 billion to healthcare providers to adopt HIT such as EHR to improve quality and reduce cost (Lin et al., 2019). Before the Act's implementation, between 9 and 30% of hospitals in the United States were using some form of HIT (Holmgren et al., 2017). However, by 2016, approximately 90% of hospitals had adopted at least a basic form of HIT (Atasoy et al., 2019). Although there has been a significant increase in the number of hospitals that have adopted HIT (Atasoy et al., 2019), there are variations in the technologies' capability or maturity. Variations in maturity make it difficult for researchers to analyze the full impact of technology on quality measures such as excess readmissions (Kulaylat et al., 2018).

Readmissions are considered an indicator of poor-quality healthcare, and they pose a financial burden on the healthcare system (Kulaylat et al., 2018). As a result, CMS enacted the HRRP in 2012 to financially penalize acute-care hospitals for excessive 30-day readmissions for six targeted conditions (NEJM Catalyst, 2018). The HRRP compares a hospital’s 30-day readmission ratio to the national average and computes an ERR. Hospitals with an ERR greater than 1 are penalized up to 3% of Medicare reimbursement (NEJM Catalyst, 2018). Other researchers have examined 14-day and 90-day readmissions related to specific quality measures; however, in this research I utilized the HRRP 30-day ERR to explore the relationship between hospitals' EHR maturity and ERR, as well as the relationship between hospital characteristics, such as hospitals’ location and the number of licensed beds and ERR.

Although there have been reductions in ERR since the implementation of the HRRP, the full impact of the HRRP on readmissions remains unclear and controversial (NEJM Catalyst, 2018). Critics of the HRRP argue that reductions in ERR since the HRRP provide little evidence of how the reductions were achieved (Fonarow, 2018). In this study, I attempted to find a relationship, if any, between hospitals’ EHR maturity and ERR, which may provide researchers and healthcare administrators with insight on how to reduce readmissions.

## Problem Statement

Variation exists in the capability or maturity of HIT in many U.S. hospitals (Tarhan et al., 2020). Some hospitals have adopted EHR with full capabilities, including external health information exchanges (HIE) to share and receive information, data analytics, disaster recovery, privacy, and security. Other hospitals have adopted EHR with only basic functions, security programs, and internal operability (Chong et al., 2020). Gomes and Romão (2018) posited that immature organizations rely on individual contributions to achieve success when adopting new technology, while mature organizations utilize systematic processes to support the adoption and implementation of an innovation. The available literature supports the adoption of HIT, such as the EHR, in hospitals to improve quality care (Martin et al., 2018). However, the variation in EHR maturity makes it difficult for researchers to assess the full impact on quality outcomes such as readmissions (Martin et al., 2018).

The National Quality Forum (NQF) has deemed readmissions a healthcare quality problem in the United States (Kulaylat et al., 2018). Sharma et al. (2018) estimated that 20% of Medicare patients are readmitted to the hospital within 30 days of discharge, with 90% of these readmissions unplanned, costing Medicare alone about $17.8 billion a year (CMS, 2018a). The adoption of EHR also costs the U.S. healthcare system about $14.5 billion in 2019 and is projected to total $19.9 billion by 2024 (Jercich, 2020).

The HITECH Act incentivized and promoted EHR adoption in healthcare to improve care quality and reduce care costs (Atasoy et al., 2019). However, there is no available information on how EHR maturity and hospital characteristics impact ERR for hospitals with Medicare patients with CABG, TKA, and THA or how hospital characteristics affect EHR maturity (van Poelgeest et al., 2017). Kharrazi et al. (2018) suggested that EHR maturity is important because each stage of maturity moves the hospital toward optimizing technology that supports patient care and improves decision support and interoperability. Mature EHR and optimized technology could improve quality care and potentially decrease readmissions. Additionally, the study of hospital characteristics is crucial to explain why some hospitals are quick to adopt mature EHR and others are slow to adopt or do not adopt at all. In this research, I went beyond the adoption of EHR and the penalties of the HRRP by analyzing the gap between hospitals' EHR maturity, hospital characteristics, and ERR for the procedure-specific conditions of the HRRP.

## Purpose of the Study

The purpose of this quantitative study was to examine a relationship, if any, between hospitals' EHR maturity and ERR. The population was hospitals with Medicare patients with the procedure-specific conditions of the HRRP. Additionally, I examined if hospital characteristics, such as hospitals' location (micropolitan or metropolitan) and the number of licensed beds, impacted EHR maturity and predict ERR. The independent variable was EHR maturity, and the dependent variables were ERR and hospital characteristics, such as hospitals' location (micropolitan or metropolitan) and number of licensed beds. The results of this research could inform hospital administrators, CMS, and other federal agencies about the need for resources that support investment in EHR maturity to reduce hospital ERR and improve healthcare quality care. Table 1 provides a summary of the study variables and population.

**Table 1**

*Variables and Population*

| Independent variable | Dependent variable | Dependent variable | Population |
|---|---|---|---|
| EHR maturity<br>EMRAM Stage 6<br>EMRAM Stage 7 | ERR 30 days | Hospital characteristics<br>Location (micropolitan, metropolitan)<br><br>Number of licensed beds (1 – 399, ≥400) | Medicare-participating hospitals<br><br>HRRP-targeted surgical conditions (CABG, THA/TKA) |

*Note*. EHR = electronic health record; EMRAM = electronic medical record adoption model; ERR = excess readmission ratio; HRRP = Hospital Readmissions Reduction Program; CABG = coronary artery bypass graft; THA/TKA = elective primary total hip or total knee arthroplasty.

## Research Questions and Hypotheses

I sought to answer three research questions. The RQs and their corresponding hypotheses were as follows:

RQ1: Is there a relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' ERR for CABG or TKA/THA among Medicare patients?

$H_0$1: There is no statistically significant relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' ERR for CABG or TKA/THA among Medicare patients.

$H_a$1: There is a statistically significant relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' ERR for CABG or TKA/THA among Medicare patients.

RQ2: Is there a relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' characteristics (hospitals' location or number of licensed beds)?

$H_0$2: There is no statistically significant relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' characteristics (hospitals' location or number of licensed beds).

$H_a$2: There is a statistically significant relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' characteristics (hospitals' location or number of licensed beds).

RQ3: Do hospitals' EHR maturity and characteristics (hospitals' location or the number of licensed beds) predict the ERR for CABG or THA/TKA among Medicare patients?

$H_0$3: There is no statistically significant relationship between hospitals' EHR maturity and characteristics (hospitals' location or the number of licensed beds) to predict the ERR for CABG or THA/TKA among Medicare patients.

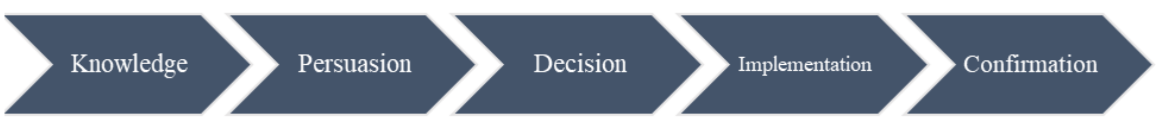
$H_a3$: There is a statistically significant relationship between hospitals' EHR maturity and characteristics (hospitals' location or the number of licensed beds) to predict the ERR for CABG or THA/TKA among Medicare patients.

## Theoretical Foundation

Everett Rogers's (1983) diffusion of innovation (DOI) was the theoretical framework for this research. Researchers in several academic disciplines, including education, sociology, geography, communication, and business, have applied the DOI theory to study various technological innovations (Akça & Özer, 2014). This theory explains the characteristics that impact the rate of diffusion or the spread of a new idea or innovation (Rogers, 1983). Rogers identified five stages of diffusion. As depicted in Figure 1, the stages include knowledge (the exposure to the innovation), persuasion (attitude about the innovation), decision (adopting or rejecting the innovation), implementation (utilizing the innovation), and confirmation (the choice to continue using innovation (Esdar et al., 2019). From these five stages, one can track how innovation is introduced to and used in a social system. Understanding these five stages is useful for understanding the barriers to adopting new technologies.

**Figure 1**

*Rogers's Five Stages of the Diffusion of Innovation*




*Note*. Original adaptaion based on Rogers (1983).

The implementation of new technology can be slow and costly and requires buy-in from all users (Lin et al., 2020). According to Rogers (1983), earlier adopters of innovations, from individuals to organizations to nations, tend to be of a higher socioeconomic status than later adopters, suggesting that socioeconomic status also plays a role in the adoption rate. This suggestion by Rogers implied that academic and urban hospitals could be early adopters of advanced technology. Because new technologies are continually emerging in healthcare, understanding factors impacting adoption and the process of diffusion is essential, as people and organizations are often hesitant to change (Cain & Mittman, 2002).

Not only is it essential to track the progress of innovation, but users must also conclude that innovation is better than the previous system (Akça & Özer, 2014). That is, adopters must be willing to change. Rogers (1983) identified five factors that impact the rate of adoption. They are relative advantage (the innovation is perceived to be better than previous ideas), compatibility (how consistent innovation is with the adopter's values, experience, and needs), complexity (how difficult innovation is to understand), trialability (to what extent an innovation can be experimented on), and observability (how much others can observe an innovation). The user’s experience with innovation, organizational, and environmental characteristics (such as technical compatibility, senior management support, and competitive pressure) is essential for accelerating the innovation's adoption. For example, the user’s ability to implement the innovation and find relative advantage plays a critical role in applying enterprise resource planning for companies (Akça & Özer, 2014). Likewise, healthcare workers' ability to collaborate and make workarounds during adoption contributes to higher relative advantage perceptions. Collaboration amongst users plays a crucial role in effectively utilizing innovation (Barrett & Stephens, 2017).

Using the DOI theory allows researchers to predict the extent of innovation diffusion based on organizational characteristics (Sadoughi et al., 2018). Rogers (1983) suggested five factors that impact the adoption of an innovation:

- individual factors (users testing the innovation on their own)
- innovative factors (users assessing the utility of the innovation)
- task factors (users' satisfaction or resistance)
- organizational factors (management hierarchy and size of the organization)
- environmental factors (cultural values and findings)

For example, Kharazzi et al. (2018) used the DOI theory and Frank Bass's diffusion model to predict EHR maturation. The Bass diffusion model predicts the extent to which a market or sector will adopt higher, better functioning innovations in the future and track progression through the five stages of diffusion. Kharazzi et al. (2018) predicted, using the two theories, that most U.S. hospitals will not reach the highest EMRAM maturity (Stage 7) until 2035 if there are no primary policy or technological changes. Specific hospital characteristics may influence EHR adoption, including potential penalties such as associated with HRRP. Because the DOI theory tracks the growth of innovation, it can be used to analyze the progress that hospitals make in moving through the EMRAM stages of maturity. The diffusion model results from Kharrazi et al. (2018), while theoretical, are essential to predicting the projected path of

EHR adoption based on the organization’s current characteristics and thus provide policy makers with ideas that can support the innovation's spread.

Although the DOI framework has benefits, some researchers have identified challenges to this theory. In assessing qualitative and quantitative data related to the diffusion of three innovations, including accountable care organizations (ACOs), advanced primary care, and EvidenceNow, Dorr et al. (2018) concluded that while adoption of innovations has occurred in these three large-scale healthcare delivery models, there are variations in how that data was utilized and shared. As a result, data could not be analyzed, utilized, or shared to drive innovations’ success. Furthermore, the data were expensive, and database corrections were time-consuming. Dorr et al. noted that while HIT adoption was significant, it was deficient in meeting the innovation goals. Therefore, different policy measures could facilitate the diffusion of HIT innovations to improve healthcare quality.

The DOI theory suggests specific characteristics of both the innovation and the adopter that affect the adoption rate. The theory also allows adopters to track the innovation's effectiveness and results through the five stages of diffusion. In this study, I considered these five stages to address the first research question concerning whether EHR maturity impacts readmission rates for specific conditions. Furthermore, the research’s second and third questions concerned a relationship between EHR maturity and hospital characteristics such as location and number of licensed beds. The use of DOI theory was essential in this research because it considers factors and characteristics necessary for the adoption and spread of the innovation, such as mature EHR (Akça & Özer, 2014).

## Nature of the Study

In this research, I used the quantitative method using secondary data from the HIMSS Analytics database and CMS website to examine the relationship between hospitals' EHR maturity (the independent variable) and hospitals' ERR (the dependent variable) among the study population of Medicare patients with CABG or THA/TKA (Curtis et al., 2016). Quantitative research assumes a postpositive philosophy with a deterministic philosophy, which suggests that a researcher can test and identify causes by influencing outcomes (Creswell, 2014). Use of the quantitative method offers a means of statistically testing numeric data to find relationships between two or more variables or to make predictions about the relationship between variables (Farghaly, 2018). The use of the quantitative method fit with the purpose of the study.

I measured the independent variable using the EMRAM, an international standard developed by HIMSS Analytics, and used by over 9,000 hospitals worldwide to measure hospitals' EHR maturity on a scale from 0 to 7 (Gomes & Romão, 2018). van Poelgeest et al. (2015, 2017) used the EMRAM maturity model in two separate studies in the Netherlands. In one study, they examined the effect of EHR maturity on overall patient safety and quality, and, in the other study, they examined the effect on the length of stay. In this study, I measured the dependent variable, excess readmissions, using the HRRP ERR. The ERR is a methodology developed by the CMS to measure hospitals' readmissions ratios for Medicare patients impacted by the targeted conditions of the

HRRP (CMS, n.d.-b). I also examined whether hospital characteristics (dependent variable), such as hospitals' location (micropolitan or metropolitan) and the number of licensed beds, impact hospitals' ERR, and if hospital characteristics predict EHR maturity or ERR.

I analyzed data using a chi-square test and logistic regression. The most appropriate statistical analysis for RQ1 and RQ2 was a chi-square test, as this is used to test the relationship, if any, between two variables (Pandis, 2016). Because the dependent variable was coded as a binary variable, the most appropriate statistical analysis for RQ3 was a logistic regression. Logistic regression is used to predict categorical dependent variables (Hamid et al., 2018).

## Literature Search Strategy

I found the reviewed articles primarily through a digital search of scholarly databases, including the Journal of the American Medical Association, MEDLINE, Medscape, ProQuest Dissertations & Theses Global, CINAHL, PsycINFO, Google Scholar, UpToDate, BMJ, Articles+, and the EBSCO Discovery Service. The search was performed for the period 2016-2020. I used the following key words, both individually and in combination: *readmissions*, *readmissions in the United States*, *care coordination*, *health information technology*, *diffusion of innovation(s)*, *electronic health record(s)*, *EHR maturity*, *maturity*, *maturity models*, *meaningful use*, *maturity and readmissions*, *EMRAM*, and *excess readmission ratio*. I accessed these resources from the Walden University Library, Princeton University Library, New York University Library, and Google Scholar.

The outline for the literature review includes a history of health information technology, a discussion about the concept of maturity, an overview of the EHR and its impact on healthcare quality, a review of four maturity models, and a discussion of readmissions as a quality problem. The literature review also includes a description of the Medicare population and an explanation for why I chose this population for the research. In the last section, I will summarize the literature and the gap in the literature.

## Literature Review Related to Key Variables and/or Concepts

Mature EHR has taken on more urgency as a way to reduce hospital readmissions considering the importance of (a) improving the quality of care and decreasing excess readmissions and (b) reducing Medicare spending, which amounted to $3.0 trillion in 2017 (MedPac, 2019). However, there is a paucity of information in the literature regarding the impact of the hospitals' EHR maturity (independent variable) on excess readmissions (dependent variable) in Medicare patients with surgical conditions of the HRRP (population). This research on EHR maturity should enable researchers to determine the impact of advanced technology on the ERR (Marshall & Lam, 2020).

### Health Information Technology and Electronic Health Records

*HIT* is a broad term that describes using electronic means to collect, view, and share health data (Samal et al., 2016). The adoption of HIT in healthcare has expanded since the Institute of Medicine's (IOM) 1991 report recommending the adoption of HIT to improve the quality of care (Kruse & Beane, 2018). A legislative expansion of the IOM recommendation was the HITECH Act of 2009 (Lin et al., 2019). The law created many national healthcare reform goals, including that healthcare providers should adopt HIT, such as EHR, to improve healthcare quality (HealthcareIT News, n.d.).

The EHR is a digitized medical chart that supports patient care and decision-making (Atasoy et al., 2019). The IOM defines a comprehensive EHR as having eight core functionalities: health information and data, result management, order entry/management, decision support, electronic communication and connectivity, patient support, administrative processes and reporting, and reporting and population health management (Kim et al., 2019). The adoption of EHR by hospitals in the United States had undergone significant transformation since the 1960s and 1970s when they were first implemented primarily by academic medical centers to store patient records electronically (Atasoy et al., 2019; Hamade et al., 2019). EHR became more popular at the beginning of the 21st century as the potential benefits of improving quality, organizing patient healthcare records, and increasing the ability and ease of medical professionals to coordinate care became more evident (Hamade et al., 2019). The use of EHR in the United States has been increasing, from 9% of hospitals using EHR in 2008 to 96% of hospitals in 2015 (Kim et al., 2019). In optimizing the sharing of health data, EHR can take on multiple forms, including multiple vendors.

Leaders of healthcare facilities can choose from a variety of vendors to implement an EHR. Although academic institutions developed many EHR in the 1960s and 1970s, vendors have been making most of the EHR since 1992 (Evans, 2016). In 2015, some of the most widely used EHR vendors included Epic (used by 27.4% of hospitals), Cerner (25.1%), MEDITECH (19.6%), McKesson (9.8%), MEDHOST (7.6%), Healthland

(4.9%), and Allscripts (4.2%; Holmgren et al., 2017). Healthcare organizations may choose to adopt an EHR from only one vendor from multiple vendors (Evans, 2016). In 2015, 54.8% of U.S. hospitals received all their products from one EHR vendor, and 45.2% used multiple vendors (Holmgren et al., 2017). EHR can vary in their design, from graphical displays to functionalities and capabilities (Yuan et al., 2019; Holmgren et al., 2017). Because of the variations in EHR capabilities, Vest et al. (2019) suggested that health systems adopted from a single EHR may have improved access to information than health systems that utilize multiple vendors. The choice and cost of EHR vendor may thus play a role in the ease of EHR adoption.

The HITECH Act financially incentivized U.S. hospitals and healthcare providers to adopt HIT, but EHR adoption has remained expensive. The cost to the U.S. healthcare system for EHR adoption was about $14.5 billion in 2019 and is estimated to cost $19.9 billion annually by 2024 (Jercich, 2020). However, Hillestad et al. (2005) predicted that the widespread adoption of EHR in the U.S. healthcare system could result in savings of nearly $100 billion annually, and Lammers and McLaughlin (2016) found that hospitals and physicians who adopted EHR technology between 2010 and 2013 saw steeper decreases in expenditures per Medicare beneficiary. However, in performing a systematic review of six articles written from 2010 to 2015, Reis et al. (2017) could not find evidence that the use of electronic interventions significantly impacted hospitals' cost-efficiency, even though the review did find some benefits in the quality of care provided by those hospital EHRs. More research would provide information on the cost-benefit of EHR adoption.

Hamade et al. (2019) suggested that hospitals that have adopted EHR have only introduced EHR into healthcare practice, whereas the hospitals using EHR have introduced the records and are actively using them to complete tasks in the healthcare system. In other words, while EHR adoption may be increasing, the systems are not always being used to their fullest potential (Collier, 2015). For example, although 48% of U.S. office-based physicians reported that they used EHR in their work in 2009, only 1.5% of U.S. hospitals were using a “comprehensive” EHR; 7.6% used a more basic system, and 17% only used computerized provider-order entry (Kim et al., 2019). Collier (2015) argued that effective use of EHR would be possible once physicians use EHR in their full capacity to communicate amongst multiple systems instead of solely within their healthcare organization. Examining the effects of these variations in using EHR on medical outcomes could have significant implications for assessing EHR maturity's impact on quality.

**The Concept of Maturity**

Healthcare systems that are using technology in advanced ways are said to have reached maturity, a concept that is important in assessing the capability of the innovation (Chong et al., 2020). Smaller hospitals and those in rural communities appear to be less likely to use technology, highlighting what Adler-Milstein et al. (2017) refer to as the “digital advanced use divide” (p. 1143). With differing levels of maturity across hospitals, the results generated from the adoption of HIT are not likely to be uniform. Understanding how maturity models can support consistency and reduce variation is essential to assess the impact on quality outcomes and innovation diffusion.

The term *maturity* describes the growth of innovation (Tarhan et al., 2020). Maturity is measured by maturity models, which can vary based on the focus and variables involved in the evolution (Carvalho et al., 2019). Tarhan et al. (2020) described maturity as a capability framework with stages (or levels) of growth and processes towards complete proficiency of the technology to improve health practices, operations, and infrastructure. Kharrazi et al. (2018) supported Tarhan et al. and described maturity as stages, with higher stages indicating the technology's optimization. A more mature innovation was adopted and improved to be better or more complete, based on predetermined conditions (Tarhan et al., 2020). Therefore, maturity models are essential to assess the growth of the innovation or reasons for failure to adopt and provide insight into improvements needed to support innovation diffusion (Gandhi & Sucahyo, 2020).

The researchers Cyrus Gibson and Richard Nolan introduced the concept of maturity to control how information systems function in the 1970s, and since then maturity models have found usage in various fields (Sarmento dos Santos-Neto & Costa, 2019). Maturity models have been used in various technological industries to provide guidance and pathways that organizations can follow to achieve full capability (Serrano & Pereira, 2020). Bertolini et al. (2019) found that 70% of the literature on maturity published between 2002 and 2019 was from 2012 to 2019, suggesting a more recent robust interest in the concept of maturity and maturity models.

However, despite the benefits of maturity models, there are challenges in their utilization. Systematic literature reviews performed by Sarmento dos Santos-Neto and Costa (2019) and Teichert (2019) confirmed that there were few agreed-upon procedures to define maturity. Linhart et al. (2017) bolstered the observations of Sarmento dos Santos-Neto and Costa and Teichert, citing that maturity models do not provide clear guidance for how organizations should prioritize improvement measures to achieve the next level of maturity. Furthermore, maturity models frequently lack features that would make them successful (Serrano & Pereira, 2020). Rabii et al. (2020) noted that cybersecurity maturity models do not have implementation recommendations, leading to uncertain results for analysis purposes. These researchers' observations point to the challenges of using maturity models. The challenges of applying maturity models apply to healthcare as well. Blondiau et al. (2016) found that most of the literature available on maturity models used in hospital settings emphasizes creating many models but rarely focuses on validating these models' implementation and deployment. Nevertheless, mature technology is vital in hospitals, because as Kharrazi et al. (2018) suggested, each stage of maturity moves the hospital toward the optimization of technology to support patient care, improve quality care, improve decision support, and enhance interoperability. Therefore, despite their disadvantages, maturity models are still worth pursuing in healthcare.

Gomes and Romão (2018) suggested that immature organizations rely on individual contributions to achieve success, while mature organizations utilize systematic processes to support the adoption and implementation of an innovation. Tarhan et al. (2020), in agreeing with Gomes and Romão (2018), posited that healthcare practices' operational maturity directly impacts healthcare services' efficiency and quality. The use of maturity models can help healthcare organizations define goals, identify strengths and weaknesses of the information technology innovation, and identify ways for quality improvement (Carvalho et al., 2018; Tarhan et al., 2020).

The association between maturity and quality care in U.S. hospitals has provided unclear results. Martin et al. (2018) performed a multivariable regression to examine the association between the English National Health Service hospitals' organizational maturity and various quality indexes. Some of those indexes included harm-free patient care episodes, hospital-level mortality index, readmission risk, complications of care, and risk of an extended length of stay. Using the NHS Clinical Digital Maturity index as a measure of maturity, Martin et al. found a significant association ($p = .014$, and $p = .033$, respectively) between organizational digital maturity, the relative risk of an extended length of stay, and the provision of harm-free care. Furthermore, mature hospitals tend to have more patients with a risk-adjusted long length of stay. However, the researchers found no significant association ($p = .796$) between organizational digital maturity and patient episodes featuring complications of care; no clear relationship ($p = .454$) between organizational digital maturity and risk-adjusted 30-day mortality, and no significant association ($p = .358$) between organizational digital maturity and the risk of readmission. Martin et al. explained that institutional factors other than organizational digital maturity may significantly impact the improvement of clinical outcomes; organizational digital maturity may only support these institutional factors. Nevertheless, these research results are not inherently transferable to a United States context, as the research focused on hospitals in England with a different healthcare system than the United States. The complexity of maturity models and the relationship between organizational characteristics, digital technology, and clinical outcomes requires further study (Martin et al., 2018).

## Electronic Health Records Maturity Models

The study of mature EHR could enable researchers to determine the impact of technology on quality care metrics (Marshall & Lam, 2020). Although there are several maturity models used in healthcare (Carvalho et al., 2016), many of these models are at an early stage of development and are not yet analyzed for efficacy (Carvalho et al., 2018). However, these models have become important in guiding organizational change (Blondiau et al., 2016). Some maturity models include the Promoting Interoperability (previously called meaningful use [MU])**,** the continuity of care maturity model (CCMM), EMR Maturity Model (EMM), and the Electronic Medical Records Adoption Model (EMRAM). I will discuss these models to explain the most effective model for this study.

### *Promoting Interoperability (Previously Called Meaningful Use)*

CMS established this model in 2011 to promote using certified electronic health record technology (CEHRT). In April 2018, CMS renamed this EHR incentive program to Promoting Interoperability and shifted the program's goals from EHR adoption and use to interoperability and better patient access (CMS, 2020e). Promoting Interoperability has five pillars for healthcare outcomes (improving quality of care, increasing patient satisfaction, reducing healthcare disparities, and ensuring electronic privacy and security) and three phases that move the practice from simply electronically exchanging health data to using advanced CEHRT to improve healthcare outcomes (Gomes & Romão, 2018). Each phase of this model provides guidelines to achieve the next level of maturity. Phase one is paper and image-driven; phase two uses less paper and includes access to internal interoperability, and phase three provides complete access to an electronic record and data sharing (Gomes & Romão, 2018). Factors such as access, interoperability, content features, organizational strategy, and goals influence this model (Gomes & Romão, 2018).

The premise of this model is that variations in hospital organizational management and IT infrastructure may not always allow for an all-or-nothing IT approach (Gomes & Romão, 2018). The process of HIT adoption in a hospital may take years and could be subject to multiple factors, including staffing, mission, and goals of the organization, as well as available financial resources. Because this model has limited maturity phases, a hospital may be somewhere between two phases, leading to confusion about the hospital's progress and the steps a hospital may have taken toward maturation (Gomes & Romão, 2018).

***Continuity of Care Maturity Model (CCMM)***

The continuity of care maturity model (CCMM) focuses on population health outcomes. Developed by HIMSS Analytics, it is an eight-staged model that supports patient-centered healthcare and population health management (Gomes & Romão, 2018). Organizations start at Stage 0 with limited or no electronic communication, and mature to stage seven, optimizing the EHR to support coordinated patient-centered healthcare through multi-organizational interconnected healthcare delivery (Gomes & Romão, 2018). The broader focus of CCMM is using information systems to improve general population health, not the quality-of-care metrics such as readmissions (Gomes & Romão, 2018).

### *EMR Maturity Model (EMM)*

Although the majority of EHR maturity measurement models are not validated, Chong et al. (2020) developed a validated maturity measurement model called the EMR (or electronic medical record) Maturity Model (EMM). The EMM is based on three functional areas (practice management, information management, and diagnosis and treatment support) intended to move the organization through six levels of maturity: Level Zero: paper; Level One: enter data; Level Two: early data use; Level Three: look ahead/predict; Level Four: population data use and Level Five: integrate. Using survey data from Ontario's community-based physicians to develop a validated model, Chong et al. hypothesized that physicians would be best at assessing maturity levels. Chong et al.'s alpha tests for correlation yielded a significance or alpha value of $\alpha$ 0.86, indicating reliability across all key measures. However, while the researchers' findings seem to confirm the tool's validity, they admit that the survey had a low response rate, and that their statistical and qualitative analysis methods could be improved. Of the Ontario-based physicians who responded, the majority were at Level Two or below. The model's small scope limits this maturity model for community-based physicians in a city in Canada, and it is unknown how its measure of maturity would translate to a larger U.S. hospital.

### *Electronic Medical Records Adoption Model (EMRAM)*

The EMRAM is one of the most effective maturity models to measure the adoption capabilities for EHR in hospitals (Gomes & Romão, 2018). Over 9,000 hospitals worldwide use EMRAM to measure maturity (Gomes & Romão, 2018). Similar to CCMM, EMRAM is developed by HIMSS Analytics and is an eight-staged model. However, unlike CCMM, EMRAM scores the maturity of the hospitals' adoption and utilization of the EHR rather than population health (Gomes & Romão, 2018). Hospitals are scored from Stage 0 to Stage 7 (see Table 2). Stage 0 represents no electronic capability and no installation of any ancillary electronic system (laboratory, pharmacy, and radiology), ascending to Stage 7, an entirely paperless environment where all aspects of patient care, privacy, and disaster recovery are managed electronically (HIMSS Analytics, 2017b). The EMRAM model is the most appropriate maturity model to measure maturity in hospitals.

The trajectory towards hospitals' full EHR maturation suggests that most U.S. hospitals will not reach Stage 7 until 2035 without any new significant policy changes (Kharrazi et al., 2018). Kharrazi et al. (2018) examined 5,200 hospitals from 2006 to 2014 using EMRAM measurements. In 2014, only 31% of hospitals were at Stage 3, compared to 96% of hospitals in 2006. On the other hand, 68% of hospitals were at Stage 4 or above compared to 4% of hospitals in 2004 (Kharrazi et al., 2018), suggesting that hospitals move towards maturation without any clear guidance or national policies.

van Poelgeest et al. (2015) performed a literature review, using EMRAM, and found a negative correlation (-0.223) between hospitals' EHR maturity score and overall safety and quality, as measured by the Elsevier hospital scoring model. The researchers noted that this negative correlation may have occurred for several reasons, including the Elsevier model's limitations to score performances properly. Furthermore, the researchers were studying hospitals in the Netherlands, and no Dutch hospital at that time had attained EMRAM Stage 7. van Poelgeest et al. (2017) performed another study using multivariate regression and found that length of stay in the hospital decreased with a higher EMRAM stage. However, there was no Dutch hospital at EMRAM Stage 7 (van Poelgeest et al., 2017). Martin et al. (2018) found no significant association ($p$ = .358) between organizational digital maturity and readmission risk. Using the NHS Clinical Digital Maturity Index to measure maturity, Martin et al. (2018) focused only on hospitals in England. While positive outcomes are associated with EHR maturity, the studies were limited in scope and location and, therefore, cannot be used to make any generalizations about the impact of EHR maturity on quality care.

**Table 2**

*HIMSS Electronic Medical Record Cumulative Capabilities (HIMSS Analytics, 2017a)*

| Stage | Definition |
|---|---|
| Stage 7 | Complete EMR, external HIE, data analytics, governance, disaster recovery, privacy, and security |
| Stage 6 | Technology enabled medication, blood products, and human milk administration, risk reporting, full CDS |
| Stage 5 | Physician documentation using structured templates, intrusion/device protection |
| Stage 4 | Computerized practitioner order entry with clinical decision support (CDS), nursing, and allied health documentation, basic business continuity |
| Stage 3 | Nursing and allied health documentation, eMAR, role-based security |
| Stage 2 | Clinical data repository, internal interoperability, basic security |
| Stage 1 | All three ancillaries installed: laboratory, pharmacy, and radiology/cardiology information systems, digital non-DICOM image management |
| Stage 0 | All three ancillaries (installation laboratory, pharmacy, and radiology systems) not installed |

**Hospital Characteristics**

Previous research suggests that hospital characteristics such as the hospitals' location and the number of licensed beds influence EHR adoption. Larger hospitals may have more extensive networks and infrastructure for technological advancement and have more financial capital to expand technological infrastructure (Lin et al., 2019). Mature EHR is less likely to be found in smaller hospitals and hospitals located in rural areas ($p < .001$) (Haggstrom et al., 2019). Although 44.5% of urban hospitals had adopted a comprehensive EHR and were actively using the EHR, only 31.7% of rural hospitals had done so (Adler-Milstein et al., 2017). Haggstrom et al. (2019) found that patients who reside in rural areas are less likely to utilize electronic means for messaging than patients in urban areas (28.3% vs. 34.5%, $p = 0.045$) or to access medical records electronically (57.5% vs. 67.1%, $p = 0.003$). Adler-Milstein et al. (2017) found that small hospitals in rural areas are significantly less likely than other hospitals to have implemented advanced EHR technology ($p < .001$). These differences may exist for many reasons, including limited access to broadband internet, high costs, and an overall lack of physician cooperation (Adler-Milstein et al., 2017).

According to Lin et al. (2019), the quality benefits of EHR use varied among hospital characteristics. Small and rural hospitals saw the largest increases in quality (0.751%, $p < .01$ for small hospitals, 0.716%, $p < .01$ for rural hospitals). Rural hospitals were the only hospitals to see significant increases in quality (0.547%, $p < .05$), but Lin et al. (2019) believed this was because of a loss of statistical power due to the reduced sample size. Additionally, Lin et al. (2019) examined the relationship between mature

EHR and hospital mortality and found that characteristics such as hospitals' location, teaching status, and size contributed to quality outcomes on three HRRP conditions: acute myocardial infarction (AMI), heart failure (HF), and pneumonia. However, the study did not provide information on how EHR maturity impacted readmissions (Lin et al., 2019). Regarding hospital characteristics that may impact readmissions, Kurtz et al. (2016) found that geography, hospital procedure volume, and nonprofit ownership were the only hospital factors that had an impact on hospital readmissions for patients undergoing THA; teaching status, location, and size of the hospital did not have a measurable association on hospital readmission. As such, there is a need to examine hospital characteristics' influence on EHR maturity.

## Electronic Health Records and Quality Care

The NQF, a not-for-profit organization that provides healthcare guidance regarding quality care to the Department of Health and Human Services in the United States, considers readmissions a quality problem (Kulaylat et al., 2018). Kulaylat et al. (2018) agreed with the NQF and posited that readmissions indicate poor-quality healthcare, as they place the patient at risk for poor outcomes, including increased mortality. Readmissions also place a financial burden on the US healthcare delivery system (Kulaylat et al., 2018). Medicare defines readmissions as any unplanned admission to any hospital within 30 days after discharge regardless of diagnosis (NEJM Catalyst, 2018), and Zuckerman et al. (2016) define readmissions as any admission to the hospital for the same index diagnosis within 30 days of discharge. Because hospital administrators continue to struggle to find the balance between quality care and efficiency, understanding the multifaceted nature of readmissions and patterns of behavior that impact readmissions is essential to reducing readmissions.

The utilization of technology in healthcare is associated with improving quality outcomes (Kruse & Beane, 2018). Predictive models and screening tools also help to identify potential risks for readmissions. Tools such as the HOSPITAL score and the identification of seniors at risk include variables that indicate a higher probability of readmissions, such as age (in the case of the identification of seniors at risk) and patient characteristics (in the case of the HOSPITAL score; Caramello et al., 2018; Donzé et al., 2016). Additionally, the use of HIT is associated with a decrease in hospital length of stay. Oh et al. (2018) found that hospitals with no operational HIT had an average length of stay of almost 12 days, whereas hospitals with a high operational HIT had an average length of stay of five days. Langabeer and Champagne (2016) supported Oh et al. (2018) and found that sharing data via HIT can improve care coordination, decrease duplicate tests, and increase efficiency. These studies provide insight into the benefits of adopting HIT to improve quality care and medical outcomes.

However, there remains skepticism among policymakers and some healthcare professionals about the effectiveness of EHR to support quality care (Lin et al., 2019). According to Yuan et al. (2019), although some studies reported a positive association between EHR use and improvements in some quality measures, other studies either report worsening or no association. In other quality measures, Yanamadala et al. (2016), utilizing univariate regression analysis to examine discharge data from state inpatient databases, found that patients at hospitals with full EHR systems have lower rates of inpatient mortality, fewer readmissions, and fewer patient safety indicators ($p < 0.05$). However, these associations did not hold ($p > 0.05$) when considering patient factors such as demographics and comorbidities and hospital factors such as length of EMR implementation. They found no significant difference in readmission rates among surgical ($p = 0.5605$) or medical patients ($p = 0.2834$) treated at hospitals with full versus no EHR (Yanamadala et al., 2016). Yuan et al. (2019) contributed to these findings made by Yanamadala et al. (2016) by bringing further skepticism on the association of EHR use and reducing readmissions.

Researchers studying a retrospective cohort of hospitals from 2008 to 2015 and data on EHR system implementation discovered that both EHR-adopting hospitals and hospitals that did not adopt an EHR did not see substantial differences in their readmission rates (Yuan et al., 2019). For example, the HF readmission rate was 24.20% for hospitals with no EHR and 24.25% for hospitals with an EHR (Yuan et al., 2019). In another example, readmission rates for AMI were 19.47% for hospitals with no EHR and 19.51% for hospitals with EHR (Yuan et al., 2019). Like Yanamadala et al. (2016), Yuan et al. (2016) found that EHR adoption has minor effects on improving readmission rates.

Vendor selection may play a role in EHR quality. Holmgren et al. (2017) used regression models to assess the relationship between EHR vendor and hospital performance and found that of the 17 high-performing hospitals, 15 of those used Epic, one used MEDITECH, and one used an EHR from a smaller vendor. Holmgren et al. (2017) also found that the EHR vendor selection could explain 23.3% of the variation in the hospitals' performance they studied. According to Yuan et al. (2019), because EHR vendors can make different choices in certain aspects of their EHR, such as computerized physician order entry, it is plausible that these differences in EHR may explain why EHR has yielded such mixed results in studies. Because EHR varies depending on vendor selection, Holmgren et al. (2017) argued that the federal government should improve the certification process for EHR and that providers should be more knowledgeable of differences among vendors to make the best purchases for their healthcare organizations.

Despite these challenges, there is still evidence that EHR adoption can improve quality care. Atasoy et al. (2019), in an interdisciplinary overview and synthesis of the academic literature on EHR adoption, found that a comprehensive EHR can resolve communication errors such as those caused by poor handwriting. Jones et al. (2014) conducted a systematic review of 236 articles published from 2010 to 2013 to examine the quality, safety, and healthcare efficiency. The implementation of HIT was associated with better quality, safety, and efficiency outcomes. The mixed-positive effect was associated with 77% of the studies and 56% reporting positive outcomes (Jones et al., 2014). Additionally, Oh et al. (2018) analyzed the HIMSS Analytics database from 2006 to 2009 to study the relationship between HIT and the quality measures length of stay and readmissions. They found that implementing HIT applications such as patient scheduling applications led to an 18.6% decrease in 30-day readmission (Oh et al., 2018). Therefore, evidence that EHR may support quality care does exist.

Further studies provide insight specifically on the relationship between EHR adoption and readmissions. In a longitudinal analysis from 2010 to 2014 of unplanned readmissions in health systems, before and after these systems adopted an EHR, Vest et al. (2019) found that healthcare systems that adopted a single EHR vendor had a lower probability of unplanned readmissions ($p = .032$), which was equivalent to the readmission rate dropping from 15.8% to 15.0%. Lin et al. (2020), in a study of the association between the level of EHR implementation and quality in a single Taiwanese hospital, found that full EHR implementation resulted in lower inpatient mortality ($p = .049$) and 14-day readmission rates ($p < .001$) when compared to no EMR, as well as lower 48-hour postoperative mortality ($p = .001$). This difference may be because of different measurements of EHR adoption; Yanamadala et al. (2016) relied on information provided to the 2011 American Hospital Association's annual survey database, which does not assess for the maturity of hospitals' EHR. However, Lin et al. (2020) relied on one hospital's information over a multi-year period. These studies suggest that EHR may still be useful for improving quality measures such as readmissions, despite healthcare professionals and policymakers' concerns.

**Readmissions**

The United States Department of Health and Human Services, CMS, the Office of the National Coordinator for Health IT, and other federal agencies have implemented policies to reduce readmissions (Kulaylat et al., 2018). By implementing these policies, federal agencies hope to reduce inconsistency, improve healthcare quality, and curtail healthcare expenditures (Kulaylat et al., 2018). One of the government's attempts to improve quality care is enacting the Patient Protection and Affordable Care Act. Commonly called the Affordable Care Act or Obamacare, the Patient Protection and Affordable Care Act is considered the most impactful change to the United States healthcare system since the Medicare and Medicaid Act of 1965 (French et al., 2016). The legislation was enacted on March 23, 2010, to improve healthcare access, decrease cost, and improve healthcare service delivery and quality (French et al., 2016). The law created innovative models of care delivery such as ACOs and the HRRP to improve the quality of patient care, including reducing excess readmissions (CMS, 2018b).

The goal of an ACO is to provide the right care at the right time while reducing unnecessary duplication of services, preventing medical errors, improving quality, and decreasing cost (Duggal et al., 2018). When the ACO achieves these goals, the organization shares the cost savings offered through the Medicare Shared Savings Program (CMS, 2018b). However, the effectiveness of ACOs in combatting readmissions is still unclear. Duggal et al. (2018), using descriptive analysis and linear regressions, found that ACOs had limited effects on reducing readmissions for HF, AMI, and pneumonia when compared to non-ACO hospitals. For example, regarding pneumonia, ACO readmission rates decreased from 18.52% to 17.00% in Pioneer ACO hospitals, and 18.47% to 16.93% for Medicare Shared Savings Program hospitals, but for non-ACO hospitals, readmission rates decreased from 18.49% to 16.95%, indicating that results were similar for both non-ACO hospitals and ACO hospitals (Duggal et al., 2018). Schoenfeld et al. (2018) also found similar results concerning the effects of ACOs on reducing readmissions following spine surgery. Schoenfeld et al. (2018) performed a retrospective review of national Medicare claims data from 2012 to 2014 and found that treatment at an ACO or a non-ACO hospital did not significantly increase the odds of being readmitted. However, readmission rates for patients treated in ACO hospitals were at 15.3%, while readmission rates for patients treated in non-ACOs were at 12.7%, suggesting that ACOs did not perform better than non-ACOs in this regard (Schoenfeld et al., 2018). Therefore, while ACOs have affected reducing readmissions, they have not been successful (Schoenfeld et al., 2018).

CMS implemented the HRRP in 2012 to create standards that reduce variability in healthcare (Kulaylat et al., 2018). The program tracks hospitals' readmission rates for six conditions. It penalizes hospitals that have high ERR for the following six conditions: AMI, chronic obstructive pulmonary disease (COPD), HF, pneumonia, CABG, and elective primary THA/TKA (CMS, n.d.-b). CMS calculates the ERR by comparing the hospital's predicted readmission rates to expected readmission rates for similar hospitals (CMS, n.d.-b). The policy places financial penalties on hospitals with ERR above 1; the higher a hospital's ERR, the greater the penalty up to the maximum 3% (NEJM Catalyst, 2018).

A review of data suggests that readmission rates have decreased since the implementation of the HRRP. After comparing monthly rates of readmissions as well as observation-service use from October 2007 (3 years before the HRRP) to May 2015 (5 years after the HRRP) and using data from 3,387 hospitals, Zuckerman et al. (2016) found that readmission rates dropped from 21.5% to 17.8% for targeted conditions and from 15.3% to 13.1% for non-targeted conditions. Lu et al. (2016) found that smaller hospitals, rural hospitals, public hospitals, and safety-net hospitals also saw more benefit from the HRRP than their counterparts. Even though the improvements appear modest, readmission reductions' trends appear to align with the Act's implementation and the readmission penalties (Zuckerman et al., 2016). However, Khera et al. (2020) found a decrease in the readmission rate from 2008 (4 years before HRRP) to 2016 (4 years after its implementation) for HF, one of the targeted conditions of the HRRP. HF rates decreased from 23.5% in 2008 to 21.7% in 2016 (Khera et al., 2020). Furthermore, AMI readmission rates, another targeted condition of the HRRP, decreased from 19.0% in 2008 to 15.9% in 2016 (Khera et al., 2020). These reductions in readmission rates would seem to suggest the efficacy of the HRRP.

However, researchers have raised many concerns about the implementation of the HRRP. Ibrahim et al. (2019) discovered that 63.1% of the reduction in hospitals' readmission rates after implementing the HRRP was due to an increase in hospitals' coded severity, not due to an increase in quality of care. Further, the conditions of the HRRP do not account for other hospital readmissions, which would track patients admitted for the same condition to a different hospital. Failing to do so, Hekkert et al. (2019) suggested, may impede quality assessment. Many hospitals with high ERR in one year may have a decline in future years, suggesting that regression to the mean may explain fluctuating values. Joshi et al. (2019), studying Medicare beneficiaries admitted for HF, pneumonia, or AMI, discovered between 74.3% and 86.5% of hospitals' ERR improvement from year to year could be explained by regression to the mean. Joshi et al. (2019) argued that other factors, such as administrative coding practices, may impact ERR improvements, calling into question the effectiveness of the HRRP.

Additionally, critics of the HRRP suggested that while it appears that readmissions have decreased since the HRRP, implementation of the policy failed to address the impact of financial penalties on hospitals or the process that reduced readmissions. Critics argued that the program was deemed successful based on reductions in admissions alone without clear evidence of how the reductions were achieved (Fonarow, 2018). Whether the shift to alternative acute care was a deliberate strategy is unclear, as observation stays and emergency department visits also increased among Medicare beneficiaries with conditions that were not targeted by the HRRP (Khera et al., 2020). Furthermore, although Fonarow et al. (2017) did not declare that the HRRP caused increases in mortality, Jha (2018) confirmed that the incentives given to hospitals by the HRRP for decreasing readmission rates were six to 10 times greater than the incentives for decreasing mortality rates, suggesting that hospitals may have prioritized readmissions over mortality concerns. However, the government's attempt to control the escalating cost of readmissions by instituting the HRRP has generated mixed results.

Some researchers have pointed to the need to look at excess mortality, instead of excess readmissions, as a correct way of measuring the quality of care. Fonarow (2018) suggested that even though there have been reductions in readmissions for HF since the HRRP, there have also been higher mortality rates. More specifically, there has been an increase in mortality rates for Medicare patients with heart disease dating back to 2009, three years before implementing the HRRP in 2012 (Fonarow, 2018). In a different study, Fonarow et al. (2017) observed that before implementing the HRRP, 30-day risk-adjusted mortality rates for Medicare patients with HF had decreased by 16.4%; however, after the implementation of the HRRP, these rates increased by 16.5%. Wadhera et al. (2018) similarly found an increase in post-discharge mortality among patients admitted with HF and pneumonia after implementing the HRRP. However, this increase in mortality was mostly related to patients who died within 30 days of discharge without being readmitted. Khera et al. (2020) were unable to explain this continued increase in mortality rates among Medicare beneficiaries with HF. Abdul-Aziz et al. (2017) suggested that financial penalties would have altered if hospitals were penalized based on excess mortality, not excess readmissions. However, because scholars still believe that readmissions are a useful measurement of quality of care and that CMS should focus on readmissions rates as a measure of quality care (Abdul-Aziz et al., 2017), readmissions will continue to be used for this research.

Other researchers that have found flaws with the HRRP have focused on medical readmissions (HF, pneumonia, AMI) and not surgical readmissions. In 2015, CMS began accounting for readmissions involving patients undergoing THA/TKA and CABG. Thompson et al. (2016) explained that surgical readmissions may be more reliable than the medical readmissions tracked by the HRRP. They suggested that hospitals reduce readmissions for surgical procedures, as performance improvements would be more noticeable than medical conditions. According to a hierarchical logistic regression model created by Thompson et al. (2016), the median risk-standardized readmission rates for Medicare patients from 2011 to 2013 were 7.1% for patients with THA/TKA and 18.8% for patients with CABG. This finding is consistent with other studies (Feng et al., 2018; Graham et al., 2019; Saleh et al., 2019), suggesting that surgical readmissions are a valid and reliable way of measuring the quality of care.

**Medicare Population**

Medicare is the most extensive health insurance program in the United States (CMS, 2020c). As of February 2019, there were 60.6 million people enrolled in Medicare (Anderson, 2019). Of the $3 trillion spent on healthcare services in 2017, Medicare accounted for 22%, or $660 billion of that spending (MedPac, 2019, p. 3). Although Medicare patients represent the minority of the population, they account for the highest healthcare expenditures and readmission rates (Kulaylat et al., 2018).

Medicare patients undergoing CABG and THA/TKA share patterns in their patient characteristics. When it comes to Medicare patients undergoing CABG, the median age is 74 years, the majority of patients are men (67.3%) and white (90%), and most (67.6%) of the operations are urgent (McNeely et al., 2016). Case et al. (2020) discovered through a query of an institutional database that patients who undergo CABG after being diagnosed with AMI are at a higher risk of being readmitted to a hospital within 30 days, as almost 25% of such patients are readmitted within this time frame. Ward and Dasgupta (2020) performed a cohort study of around 24 million Medicare beneficiaries and found that 84.6% of patients undergoing TKA were white, with a mean age of 74.2 years. Furthermore, higher ratios of TKA were prevalent in beneficiaries with fewer outpatient visits, and more surgeons per capita performed this surgery (Ward & Dasgupta, 2020). Many patients undergoing THA were between the ages of 65 and 69 (123,690 out of 442,333), and the majority were also white (413,636 out of 442,333), according to a multilevel logistic regression analysis performed by Kurtz et al. (2016). Although there is some information available regarding patient characteristics on surgical outcomes, analysis of hospital characteristics could provide useful information regarding the impact of location and number of licensed beds on surgical readmissions.

## Summary

Despite the widespread adoption of EHR, there are significant differences in hospitals' EHR maturity in US hospitals (Atasoy et al., 2019; Samal et al., 2016). Small, rural hospitals with less bed capacity often have less advanced EHR, while larger, urban hospitals with more bed capacity typically have more advanced EHR (Adler-Milstein et al., 2017; Lin et al., 2019). Researchers and healthcare administrators have used several maturity models to assess the level of maturity of hospitals' EHR (Carvalho et al., 2016; Gandhi & Sucahyo, 2020).

Although studies suggest that EHR adoption can promote better quality healthcare, there is not much literature on the relationship between the maturity of EHR and quality outcomes (Lin et al., 2019). The HITECH Act incentivized providers to adopt EHR (Kruse & Beane, 2018; Lin et al., 2019). In contrast, the HRRP penalized hospitals for ERRs. Although the goal of the HRRP was to reduce excess readmissions, these efforts resulted in mixed outcomes (CMS, 2020b; Fonarow, 2018; French et al., 2016).

Researchers have examined readmissions rates for specific conditions since the implementation of HRRP; however, the current literature does not provide information on the impact of EHR maturity on excess readmissions among hospitals with Medicare patients with surgical conditions of the HRRP. Further study is needed to examine innovations to improve quality care, decrease costs, and reduce readmissions among the Medicare population (Hekkert et al., 2017).

## Definitions

*Avoidable readmission*: An admission to any hospital for the same index diagnosis within 30 days of discharge (Ashfaq et al., 2019).

*Electronic health records (EHR)*: Systems that allow healthcare providers to share and aggregate patient data (Marshall & Lam, 2020).

*Excess readmission ratio (ERR)*: The ratio of the predicted readmission rate and the expected readmission rate of a hospital, which CMS uses to assess hospitals' excess readmission rate (CMS, n.d.-b).

*Health information technology (HIT)*: The use of electronic means to share and view health data (Samal et al., 2016).

*Health information exchanges (HIE)*: The use of technology to electronically share and communicate medical information securely across organizational and geographical boundaries (Langabeer & Champagne, 2016).

*Index diagnosis*: The initial illness identified for a patient upon admittance to a hospital; in the context of avoidable readmissions, the patient returns to the hospital within 30 days to receive treatment for this initial illness again (Kulaylat et al., 2018).

*Interoperability*: The capability for the EHR to receive and share information electronically among other providers (Carvalho et al., 2019).

*Location*: In this study, location will refer to whether a hospital is micropolitan or metropolitan. A micropolitan hospital is in an area with a population between 10,000 and 50,000, while a metropolitan hospital is in an area with a population greater than 50,000 (U.S. Census Bureau, 2020).

*Maturity*: The optimization of a technology (Tarhan et al., 2020). A fully mature EHR suggest capabilities that support a fully electronic, paperless environment, as well as integrated electronic communication with other healthcare systems (Gomes & Romão, 2018).

*Number of licensed beds*: The number of beds that a hospital is legally able to provide to patients (Walker, 2018). Hospitals may be classified as small, medium, or large based on the number of licensed beds (Lu et al., 2016). In this study, small hospitals will have 1 – 399 licensed beds, and large hospitals will have more than 400 licensed beds.

## Assumptions

This research had two assumptions. The first assumption was that HIMSS Analytics used a consistent methodology in assigning EMRAM scores to hospitals. If, for example, two hospitals with the same technological capabilities received different EMRAM scores, it would not be possible to measure a hospital's EHR maturity level accurately. The second assumption was that hospitals accurately reported readmissions data for the HRRP's targeted conditions to CMS. If readmissions data was inaccurate, a hospital's ERR would also be inaccurate, providing an incorrect assessment of a hospital's readmission performance.

## Scope and Delimitations

In this study, I analyzed the relationship between hospitals' EHR maturity and the ERR for hospitals with Medicare patients. The study population was limited to hospitals with Medicare patients in the United States. Medicare patients extensively utilize the healthcare system and are prone to readmissions due to advancing age and comorbidities and generate high healthcare costs. Patients using Medicaid or other commercial insurances were not studied. Additionally, the impact of EHR maturity and the characteristics of the hospital on readmissions were studied. Hospital characteristics included hospitals' location and the number of licensed beds. The scope of this research was limited to the EMRAM stage of maturity from the HIMSS database and the ERR for the HRRP procedure-specific conditions from CMS. Due to a lack of robustness in other maturity models, other models of measuring EHR maturity were not used. Using data from these verifiable sources reduced the incidence of errors and supported the integrity of the data.

Additionally, because this was a quantitative study, there was no opportunity for observation, thoughts, healthcare professionals' perspectives, and opinions. Other factors, such as socioeconomic status and procedures not included in the HRRP, were not considered. The study results could be significant to healthcare administrations to generalize and predict information necessary to reduce excess readmissions among the Medicare population.

## Limitations

There were three limitations anticipated for this study. The data's reliability and validity were defined and limited by the available HIMSS and CMS secondary data sets and their process of collection and statistical manipulation of the data. Because HIMSS Analytics changed scholars' ability to access data sets from 2018 forward, this study was restricted to 2017 data to correspond with CMS data. Using data from this time frame alone may not have provided the most recent information regarding the hospital's current EMRAM stage or ERR status. Finally, because CMS and HIMSS are self-governing agencies, there was a potential for bias based on the CMS definition for ERR and how HIMSS determines EMRAM stages. However, after analyzing the variables, this research provided recommendations for future quantitative research that could capture a broader time frame regarding any predictions made during analysis.

## Significance

The answers to these RQs are significant because they can help hospital administrators make informed decisions about investments in technology that support the diffusion and spread of innovation and improve quality care throughout United States hospitals. This research is significant because it addresses the literature gap by studying the relationship between hospitals’ EHR maturity and ERR and the relationship between hospital characteristics, such as hospitals’ location and the number of licensed beds and ERR. Utilizing EMRAM stages as a guide for measuring hospitals' EHR maturity and ERR for measuring readmissions could allow for conclusions about the relationship between hospitals with advanced EHR maturity and ERR. The conclusions could also give insight on how to reduce ERR and improve healthcare quality. Finally, understanding these relationships can provide information that supports the triple aim of healthcare reform in the United States (Sheikh et al., 2015).

## Summary and Conclusions

Since the implementation of the HITECH Act, EHR adoption has become nearly universal in U.S. hospitals. However, variation exists in the adoption and maturity of the technology. Hospital characteristics such as hospitals' location and number of licensed beds may impact EHR adoption (Adler-Milstein et al., 2017; Haggstrom et al., 2019). Studies have also suggested that EHR adoption is positively associated with improving quality care outcomes, such as readmissions. According to Kulaylat et al. (2018), Medicare patients account for the highest expenditures and readmission rates. The HRRP, which aimed to reduce readmissions among Medicare beneficiaries, has yielded mixed outcomes (Fonarow, 2018). This study examined whether EHR maturity, as measured by the EMRAM stage, has any relationship to readmissions as measured by ERR. In seeking a relationship, if any, through this quantitative study, the findings may extend knowledge on reducing readmissions and improving the quality of care in hospitals with Medicare patients.

# Section 2: Research Design and Data Collection

The purpose of this quantitative study was to examine the relationship, if any, between hospitals' EHR maturity and ERR. The population was hospitals with Medicare patients with the procedure-specific conditions of the HRRP. Additionally, I examined whether hospital characteristics, such as hospitals' location (micropolitan or metropolitan) and the number of licensed beds (1-399 and 400 or more), impact EHR maturity and predict ERR. The independent variable was EHR maturity, and the dependent variables were ERR and hospital characteristics, such as hospitals' location (micropolitan or metropolitan) and number of licensed beds (1-399 and 400 or more). The results of this research could inform hospital administrators, CMS, and other federal agencies about the need for resources that support investment in EHR maturity to reduce hospital ERR and improve healthcare quality care. In this section, I explain the study's research design and rationale, the target population, sampling procedures, and power analysis used to calculate the sample size. Additionally, this section includes information on the instrumentation and operational constructs, threats to validity, and ethical procedures.

## Research Design and Rationale

I used a quantitative method using secondary data from the HIMSS Analytics database and CMS website. A quantitative method is the best method to statistically test numeric data to find patterns of relationships or make predictions among variables (Farghaly, 2018). The independent variable, EHR maturity, was measured using the HIMSS Analytics EMRAM, which scores hospitals' EHR capability on a scale from

Stage 0 to 7. The HIMSS database is the 2017 HIMSS Analytics Database, which comes from the Dorenfest Institute. The dependent variable was the ERR, which is a methodology developed by the CMS to measure hospitals' readmissions ratios for Medicare patients impacted by the targeted conditions of the HRRP (CMS, n.d.-b). The CMS calculates the ERR by comparing the hospital's predicted readmission rates to expected readmission rates for similar hospitals (CMS, n.d.-b). The name of the data set from CMS.gov is FY 2017 IPPS Final Rule: Hospital Readmissions Reduction Program Supplemental Data File. I used it to collect ERR data for the procedure-specific conditions of the HRRP.

In 2018, HIMSS Analytics changed scholars' ability to fully access their database; therefore, the most recent data available from the Dorenfest Institute is from 2017. I used CMS data from 2017 to maintain consistency with time frames. I assumed that data from 2017 would not adversely affect findings because readmissions continue to be a current issue in the U.S. healthcare system (Kulaylat et al., 2018). Collecting EHR maturity and ERR data from all United States hospitals would be logistically and financially challenging. Secondary data analysis makes managing the data more feasible (Cole & Trinh, 2017). Additionally, analysis of secondary data requires less cost and time compared to primary data. Yet, although the data collection is less expensive, there are constraints with the available data due to the inability to manipulate the data and the limited data time frame.

I used the chi-square test and logistic regression as the statistical tests to examine any potential relationship between hospitals' EHR maturity, ERR, and hospital characteristics. The most appropriate statistical analysis for RQ1 and RQ2 was a chi-square test, as this statistical procedure is best to test associations or relationships between two categorical variables (Pandis, 2016). Because the dependent variable was coded as a binary variable, the most appropriate statistical analysis for RQ3 was a logistic regression. A logistic regression is used to predict categorial dependent variables (Hamid et al., 2018). The tests' results can advance knowledge regarding how EHR maturity and hospital characteristics, such as hospitals' location (micropolitan or metropolitan) and number of licensed beds (1-399 and 400 or more), impact excess readmissions in U.S. hospitals that provide care to Medicare patients.

## Methodology

### Population

The population for this research was hospitals with Medicare patients treated for CABG and THA/TKA. As of 2019, there are 6,023 U.S. hospitals that are considered Medicare institutional providers, including short stay (3,283), psychiatric (604), rehabilitation (306), children's (95), long term (367), critical access (1,353), and religious nonmedical (15), according to CMS (2020a). These hospitals share certain characteristics. When it comes to bed size, large hospitals (more than 300 beds) tend to have more patients with both CABG and THA/TKA than smaller hospitals (Thompson et al., 2016). More specifically, 78.0% of hospitals with more than 300 beds admitted patients with CABG, and 52.2% of hospitals with more than 300 beds admitted patients with THA/TKA (Thompson et al., 2016). Meanwhile, 21.9% of hospitals with 100 to 300 beds admitted patients with CABG, and 40.5% of hospitals with the same bed size admitted patients with THA/TKA (Thompson et al., 2016). Kurtz et al. (2016) found that geography, hospital procedure volume, and nonprofit ownership were the only hospital characteristics that affected hospital readmissions for THA patients. The location and size of the hospital did not have a measurable effect on hospital readmission risk (Kurtz et al., 2016).

## Sampling and Sampling Procedures Used to Collect Data

In this research, I analyzed existing secondary data from HIMSS Analytics and CMS. CMS and HIMSS controlled the process of recruitment, participation, and data collection associated with the secondary data sets.

### *HIMSS Sampling*

The Dorenfest Institute provided access to the HIMSS database via email; no permission letters were necessary to be signed by me. Although HIMSS is not transparent about their sampling procedures, they collect their demographic and IT data from 5,407 hospitals, 2,317 subacute care facilities, 35,132 ambulatory facilities, 1,375 home health care facilities, and 180 free standing data centers. HIMSS then organizes the data into various tables in their data set. I used the HIMSS Analytics data because these data have been used in the past to measure EHR maturity using EMRAM (AlHazme et al., 2016; Hillestad et al., 2005; van Poelgeest et al., 2017).

### *CMS Sampling*

I found the CMS data set online at CMS.gov (FY 2017 IPPS Final Rule: Hospital Readmissions Reduction Program Supplemental Data File); no permission letters were necessary because the data files are available to the public. The CMS is a reputable federal agency within the United States Department of Health and Human Services with oversight and governance for healthcare and reimbursement for the Medicare population (CMS, n.d.-a). The 21st Century Cures Act of 2016 mandates that CMS assess hospital penalties based on hospitals' performance compared to similar hospitals. CMS divides the hospitals into five peer groups, or quintiles, based on the proportion of eligible Medicare patients. The median ERR of hospitals within the peer group is used as the threshold to assess hospital performance (CMS, 2017b). This data set has been used in previous years to assess excess readmissions in the United States (Caracciolo et al., 2017; Kulaylat et al., 2018; Lu et al., 2016).

***Sampling Plan***

I used probability sampling, specifically cluster sampling. I matched hospitals by the Medicare provider number for both the HIMSS data set and the CMS data set. The data were clustered based on EMRAM maturity level after ensuring that other crucial information, such as the hospital's EMRAM score, location, and number of licensed beds, were available. The HRRP's ERR penalties exclude 10 types of hospitals: children's hospitals, psychiatric hospitals, long-term care hospitals, certain cancer hospitals, veterans' affairs hospitals, hospitals with fewer than 25 discharges for the targeted conditions, rehabilitation hospitals, religious nonmedical health care institutions, and critical-access designated hospitals, which are smaller hospitals in rural areas in the United States (Kulaylat et al., 2018). I did not sample these hospitals.

The statistical procedure for RQ1 and RQ2 was the chi-square test, and the statistical procedure for RQ3 was logistic regression. I carried out an a priori sample size calculation for this study using G*Power. It was necessary to identify the inferential procedures that would be applied in the study to carry out this analysis. Because both statistical procedures are inferential, the following values were specified, guided by Cohen's (1988) recommendations. Cohen suggested that a power of 0.80 is generally accepted, which enhances the chances of finding statistically significant differences among variables.

I used a significance, or alpha, level of 0.05 to reduce the risk of a Type 1 Error. For the chi-square statistical procedure, Cohen (1988) suggested an effect size of 0.20 to be small, 0.50 to be medium, and 0.80 to be large. An effect size of 0.50 was used for this study to measure the strength of the relationship between hospitals' EHR maturity, hospital characteristics, and ERR. Cohen suggested an effect size of 0.02 to be small, 0.15 to be medium, and 0.35 to be large for the statistical regression procedure. An effect size of 0.35 was used for this study to predict the strength of the relationship between hospitals' EHR maturity, hospital characteristics, and ERR.

Based on these inputs, I conducted the a priori sample size analysis using the statistical program G*Power. A sample size of 314 hospitals was calculated, which is less than the 5,407 hospitals listed in the HIMSS database (HIMSS, 2017). Results of the power analysis are shown in Tables 3 to 6.

**Table 3**

*Sample Size Power Analysis (Chi-Square RQ1)*

| Effect size | Statistical power level | Significance level | Sample size |
|---|---|---|---|
| 0.50 | 0.80 | 0.05 | 90 |

**Table 4**

*Sample Size Power Analysis (Chi-Square RQ2, Number of Licensed Beds)*

| Effect size | Statistical power level | Significance level | Sample size |
|---|---|---|---|
| 0.50 | 0.80 | 0.05 | 84 |

**Table 5**

*Sample Size Power Analysis (Chi-Square RQ2, Hospitals' Location)*

| Effect Size | Statistical power level | Significance level | Sample size |
|---|---|---|---|
| 0.50 | 0.80 | 0.05 | 72 |

**Table 6**

*Sample Size Power Analysis (Logistic Regression RQ3)*

| Effect size | Statistical power level | Significance level | Sample size |
|---|---|---|---|
| 0.15 | 0.80 | 0.05 | 68 |

## Instrumentation and Operationalization of Constructs

HIMSS collects demographic and IT data for its data set from almost 40,000 facilities, including 5,407 hospitals (HIMSS, 2017). HIMSS uses the Dorenfest Complete Integrated Healthcare Delivery System Plus Database, a market intelligence tool initially developed by the Dorenfest Institute in 1986 (HIMSS, 2017). The HIMSS database has been used in the past to collect data from United States healthcare facilities and analyze that data (AlHazme et al., 2016; Hillestad et al., 2005; van Poelgeest et al., 2017). The HIMSS data set is extensive and includes demographic information, statistics, and summary information about hospitals, and lists of vendors used by facilities. This instrument will not be used in this study; thus, permission was not needed from the developer to use the instrument.

CMS uses the MS-DRG Grouper Software and Medicare Code Editor to collect and analyze its data for all HRRP-eligible, Medicare-certified hospitals (CMS, 2020d). The American Medical Association developed the software in 2017 (CMS, 2020d). CMS has used this software in the past to assess and classify financial penalties based on hospitals’ performance compared to similar hospitals (CMS, 2020d). The variables used to collect data were the hospital CMS certification number, dual proportion, peer group assignment, ERR, number of eligible discharges, peer group median ERR, and penalty indicator (CMS, 2017b). This instrument will also not be used in this study, and thus, no permission was needed from the developer to use the instrument.

***Operationalization for Each Variable***

The Medicare provider number found in the FY 2017 IPPS Final Rule: Hospital Readmissions Reduction Program Supplemental Data File identifies the hospital. The variable called "PROV" in this data set contains the Medicare provider number. In the 2017 HIMSS Analytics Database, the variable called “MedicareNumber” in the table HAEntity contains the Medicare provider number. HIMSS Analytics uses its methodology and algorithms to automatically score hospitals' EHR maturity based on their Electronic Medical Records (EMR) capabilities (HIMSS Analytics, 2017b). The

EMRAM scores comes from the 2017 HIMSS Analytics Database. These scores are in the table called EMRAM_StageValidation, and the variable is under the field name "Stage." "Stage" is characterized as a text, with data options between 6 and 7. EMRAM scores hospitals from Stage 0 to Stage 7. At Stage 0, hospitals have no electronic capability and no ancillary electronic system installation. At Stage 7, hospitals have an entirely paperless environment where all aspects of patient care, privacy, and disaster recovery are managed electronically. Table 2 in Section 1 represents all the stages in more detail. The HIMSS data set only included hospitals with EMRAM Stages 6 and 7, so only these two stages were used in the study. This data was used as a number and was also used to measure the EHR maturity of the selected hospitals.

The ERR is a methodology developed by CMS to measure hospitals' readmissions ratios for Medicare patients impacted by the targeted conditions of the HRRP (CMS, n.d.-b). CMS calculates the ERR by comparing the hospital's predicted readmission rates to expected readmission rates for similar hospitals (CMS, n.d.-b). CMS collects data using claims data submitted by hospitals, specifically cases related to any of the six measures (AMI, COPD, HF, pneumonia, CABG, and THA/TKA; CMS, 2020b). This data is calculated into the sum of diagnosis-related group (DRG) relative weights for each case and the transfer adjusted DRG relative weights. DRG is part of the term MS-DRG, which means Medicare Severity Diagnosis Related Groups. CMS calculates the ERR using the information gained about the hospital's performance and then calculates the payment adjustment factors using this formula,

$$\mathrm{P} = 1 - \min\left\{.03, \sum\nolimits_{\mathrm{dx}} \frac{NM_M \,\mathrm{Payment\,(dx)} * \max\{(\mathrm{ERR\,(dx)} - \boxed{\mathrm{Median}}\ \mathrm{peer\ \ group\ \ ERR\,(dx)}), 0\}}{\mathrm{All\ \ payments}}\right\}$$

"where dx is any of the six measures (AMI, COPD, HF, pneumonia, CABG, and THKA), payments are base DRG payments, and the ERR is a hospital's performance on that measure" (CMS, 2017b, p. 6). After sending their findings to the appropriate hospitals, CMS will report the HRRP data in the Inpatient Prospective Payment System/Long-Term Care Hospital Prospective Payment System Final Rule Supplemental Data File.

The FY 2017 IPPS Final Rule: Hospital Readmissions Reduction Program Supplemental Data File contains the ERR. This study focused on the ERR for THA/TKA (based on methodology finalized in the FY 2014 IPPS Final Rule and the FY 2015 IPPS Final Rule) and the ERR for CABG (based on methodology finalized in the FY 2015 IPPS Final Rule [79 FR 50033]). The variables are called CABG Excess Readmission Ratio and Total Hip/Total Knee Arthroplasty Excess Readmission Ratio in the CMS data set. This data is captured as a number between 0 and 1. An ERR above 1 was coded as 1 and an ERR less than 1 was coded as 0. An ERR above 1 indicates that a hospital’s performance was worse than that of the average hospital, and an ERR below 1 indicates that a hospital’s performance was considered average (CMS, 2017b). The CMS data set did not include ERR for hospitals in Puerto Rico and hospitals with fewer than 25 cases.

The hospital characteristics for this research were the hospitals’ location (micropolitan or metropolitan) and number of licensed beds. In the HIMSS data set, the table called HAEntity includes the hospitals’ location and number of beds. The "City" and "State" variables contain the location of the hospitals. After finding the city's population using the U.S. Census Bureau, the location was categorized based on the U.S. Census Bureau's (2020) specifications. Micropolitan hospitals are located in an area with a population between 10,000 and 50,000, and metropolitan hospitals are located in an area with a population greater than 50,000 (U.S. Census Bureau, 2020). The field name "NofBeds" contains the variable for the number of beds. A small hospital has between 1 and 399 beds, and a large hospital has 400 or more beds. The operational definitions of the variables for this study are depicted in Table 7.

**Table 7**

*Operational Definitions of Variables*

| Name | Measurement | Values of Variables |
|---|---|---|
| Hospital | Categorical | Medicare-certified acute-care hospitals (0) |
| Hospital's EHR Maturity | Ordinal | EMRAM Score Stage 6 (0)<br>EMRAM Score Stage 7 (1) |
| Hospital's ERR | Binary | 0.00 – 0.99; Better than average performance (0)<br>>1.00; Worse than average performance (1) |
| Hospital's Location | Nominal | Micropolitan (0)<br>Metropolitan (1) |
| Hospital's Number of Licensed Beds | Nominal | 1 – 399 beds (0)<br>> 400 beds (1) |

**Data Analysis Plan**

The EMRAM data was analyzed and cleaned by an internal quality department at HIMSS, consisting of a manager of four team members. CMS uses the MS-DRG Grouper Software and Medicare Code Editor to analyze and clean its data. I analyzed, cleaned, and screened the EMRAM and CMS data for this study by using IBM SPSS Statistics v. 27.0 (2020) statistical software. I removed any data unrelated to my RQs. If the Medicare provider number, ERR for either CABG or THA/TKA, EMRAM score, location, or number of licensed beds for a hospital was not available, I removed that hospital from the study. Chi-square and logistic regression were the statistical tools used to test the hypotheses. The results were interpreted using logistic regression, and the chi-square test accounted for the use of multiple statistical tests (Ali & Bhaskar, 2016). The results were also interpreted using probability values. No covariates or confounding variables were included in this research.

I sought to answer three RQs. The questions and their corresponding hypotheses were as follows:

RQ1: Is there a relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' ERR for CABG or TKA/THA among Medicare patients?

> $H_0$1: There is no statistically significant relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' ERR for CABG or TKA/THA among Medicare patients.

$H_a1$: There is a statistically significant relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' ERR for CABG or TKA/THA among Medicare patients.

RQ2: Is there a relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' characteristics (hospitals' location or number of licensed beds)?

$H_02$: There is no statistically significant relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' characteristics (hospitals' location or number of licensed beds).

$H_a2$: There is a statistically significant relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' characteristics (hospitals' location or number of licensed beds).

RQ3: Do hospitals' EHR maturity and characteristics (hospitals' location or the number of licensed beds) predict the ERR for CABG or THA/TKA among Medicare patients?

$H_03$: There is no statistically significant relationship between hospitals' EHR maturity and characteristics (hospitals' location or the number of licensed beds) to predict the ERR for CABG or THA/TKA among Medicare patients.

$H_a3$: There is a statistically significant relationship between hospitals' EHR maturity and characteristics (hospitals' location or the number of licensed beds) to predict the ERR for CABG or THA/TKA among Medicare patients.

## Threats to Validity

Threats to validity could alter a study's outcome. Internal validity is the extent to which the results represent the studied population’s truth and are thus not the result of methodological errors (Patino & Ferrerira, 2018). This research used secondary research analysis, including previously collected data. Because this kind of data is most susceptible to containing missing data and biases (Cole & Trinh, 2017), there was a possibility that the HIMSS Analytics and CMS data could have errors. Despite this possibility, these two data sets were still the most relevant for this study. Using EMRAM data from HIMSS analytics, who created the model, was most appropriate. Also, CMS should be one of the best sources for Medicare readmission data. The reputability of these data sets enhanced internal validity. Future studies may decide to use different instruments to analyze the data instead of utilizing the tools provided by CMS and HIMSS Analytics.

External validity is the extent to which results can be generalized to different variables and populations (Patino & Ferreira, 2018). This study’s RQs centered on whether a relationship exists between EHR maturity and ERR for procedure-specific conditions of the HRRP among the Medicare population. Using data from controlled trials increased the risk for selection bias and limited generalizability (Cole & Trinh, 2017). Therefore, sampling from secondary data sets from HIMSS Analytics and CMS avoided data collection and retrieval threats, allowing for more generalizability of the results (Cole & Trinh, 2017).

Threats to construct validity and statistical conclusion validity may also exist. As I sought to find a relationship between variables, if I had found no relationship between variables when there was a relationship, these results would be a threat to conclusion validity (Trochim, 2020). Conclusion validity is supported when the researcher uses reputable databases and good statistical power, preferably greater than 0.8 in value. When the researcher uses proper operations and theoretical constructs, leading to legitimate conclusions, construct validity is achieved. A potential threat to construct validity was that factors other than EHR maturity may have also impacted a change in excess readmissions (Trochim, 2020). However, the threat to construct validity was reduced by providing the operational definitions of the variables in this research and understanding how Rogers's DOI theory grounded understandings of how an adopter's characteristics may impact the rate of adopting an innovation.

**Ethical Procedures**

The data for this study came from secondary sources obtained from public databases. The CMS data is available at no cost, and the HIMSS data set is accessible by emailing the Dorenfest Institute for permission. The data was stored on my personal computer, which is password-protected. Because permission was needed to obtain the HIMSS data set, the data set will be removed from my personal computer following the completion of the study. Ethical considerations such as academic fraud and misrepresentation of data were minimized by following Walden University's research integrity policies.

This study did not utilize any human subjects or personal information. The exclusion criteria factors included types of hospitals instead of people, thus minimizing the risk of any stigma. Furthermore, the data in both databases is anonymous, and only the total amount of cases related to each procedure, based on a hospital, is known. Therefore, any ethical data collection procedures for original data collection were removed, and any ethical concerns related to humans were minimized. The Walden University Institutional Review Board (IRB) reviewed and approved the study (IRB approval number 05-18-21-0473637).

## Summary

In this research, I studied the relationship between hospitals' EHR maturity and ERR. I also examined whether the hospitals' location and number of licensed beds were associated with or predicted EHR maturity or ERR. The population studied in this research was hospitals with Medicare patients treated for CABG and elective primary THA/TKA. Understanding how a hospital's EHR maturity affects that hospital's ERR can help support hospital administrators' efforts to improve healthcare quality for hospitals with Medicare patients.

Because the aim of this research was to find patterns of relationships and make predictions among variables, a chi-square test and a logistic regression test were used in this quantitative study (Farghaly, 2018). I retrieved my data from secondary data analysis, limiting the amount of time, money, and human involvement necessary for the study. The data for the final data set came from 2017 HIMSS Analytics Database and was measured by the HIMSS Analytics EMRAM stage and the FY 2017 IPPS Final Rule:

Hospital Readmissions Reduction Program Supplemental Data File. The CMS and HIMSS data sets have been used before in similar research, thus increasing their reputability (AlHazme et al., 2016; Caracciolo et al., 2017; Hillestad et al., 2005; Kulaylat et al., 2018; Lu et al., 2016; van Poelgeest et al., 2017). Using cluster sampling allowed me to limit the data based on location and maturity to find any relationship between this research's variables. The power analysis results indicated that a sample size of 314 was most appropriate for this study. Section 3 will include the data analysis results.

# Section 3: Presentation of the Results and Findings

The purpose of this quantitative study was to analyze the relationship between EHR maturity, as measured by EMRAM stage, ERR for CABG, and ERR for THA/TKA, and hospital characteristics, such as hospitals' location (micropolitan or metropolitan) and the number of licensed beds (1-399 and 400 or more). I retrieved the sample of Medicare hospitals from the HIMSS database. Both chi-square and logistic regression analyses were used for statistical analyses. The findings of this study are included in this chapter. First, I present the frequency of the variables used in the study. Next, I present the results of the analyses for each of the three RQs and subquestions. Finally, the summary of the results is included at the end of the section.

## Data Collection of Secondary Data Set

I used HIMSS demographic data from 2017, which included 5,407 hospitals. The CMS data set was compiled in 2017 after CMS collected readmission data from Medicare-participating hospitals to calculate the ERR for HRRP-targeted conditions. The CMS data set was collected during the 2017 fiscal year; however, HIMSS does not provide any information about their data collection methods. I collected the census data from the U.S. Census Bureau's metropolitan and micropolitan statistical area population estimates for 2010 to 2019.

I obtained the final data set for this study from three data sources: HIMSS, CMS, and the U.S. Census Bureau. The combined data set for this study includes the complete HIMSS data set and the complete CMS data set, which are both representative of the population. The CMS data set contained the ERR for THA/TKA (2,919) and CABG

(1,174). The HIMSS data sets contained data for EHR maturity stage, which contained data for 11,757 providers at Stages 6 and 7. Additionally, this data set contained data for 9,908 providers regarding the number of licensed beds each provider had within their facility.

After combining the CMS and HIMSS data sets, I was able to obtain data for 1,006 Medicare-certified acute-care hospitals. The variables tested in the population included the CABG ERR, THA/TKA ERR, EMRAM stage, location, and the number of licensed beds (see Table 8). Out of the 1,006 hospitals, 350 hospitals had data for CABG ERR, and 745 hospitals had data for THA/TKA ERR. The hospitals with CABG ERR and the hospitals with THA/TKA ERR do not add up to 1,006 hospitals because they are separate variables and therefore overlapped at times. All 1,006 hospitals had complete EMRAM data and complete data on the number of licensed beds. However, of the 1,006 hospitals, I was only able to include information on the hospital's location for 993 institutions; rural hospitals were not included in the frequency count because they were not used in any of the analyses. Therefore, of the 1,006 hospitals in the complete data set, there are only 993 hospitals that provided data in terms of hospitals' location (see Table 9).

The two variables that contained the highest number of cases were EMRAM Stage 6, which contained 931 hospitals (92.5%), and EMRAM Stage 7, which contained 75 hospitals (7%). Most hospitals (84.1%) were located in metropolitan locations; 16% were located in micropolitan locations. Regarding the number of licensed beds, 78.9% of hospitals had 1-399 licensed beds, and 21.1% had more than 400 licensed beds. Initially, the ERR was a continuous variable in the CMS data set, but for the purpose of the analyses for RQ1 and RQ3, it was recoded as a binary variable. An ERR above 1 was coded as 1, and an ERR less than 1 was coded as 0. An ERR above 1 indicates that a hospital’s performance was worse than that of the average hospital, and an ERR below 1 indicates that a hospital’s performance was considered average (CMS, 2017b). Specifically, for CABG, 58.6% of hospitals had an ERR of 0, and 41.4% of hospitals had an ERR of 1. For THA/TKA, 51.5% of hospitals had an ERR of 0, and 48.5% of hospitals had an ERR of 1 (see Table 9).

Both the CMS and the HIMSS data sets contained incomplete and missing data from the hospitals surveyed. There were four discrepancies in the HIMSS data set. First, there was a lack of variance in EMRAM stages. For example, the data set only included hospitals with Stage 6 or 7 EMRAM. Also, the ERR for CABG and THA/TKA are reported separately in the data set and therefore will be addressed as distinct variables. Because there were few rural hospitals included in the HIMSS data set, I considered hospitals micropolitan or metropolitan instead of rural or urban. Micropolitan refers to hospitals located in areas with a population between 10,000 and 50,000, and metropolitan refers to hospitals located in areas with a population greater than 50,000 (U.S. Census Bureau, 2020). Furthermore, the number of licensed beds has shifted: small hospitals now have 1–399 beds, and large hospitals have 400 beds or more. Nevertheless, this data will be sufficient to answer the RQs, as the available data provide insight as to what extent the size and location of a hospital may impact a particular EMRAM stage.

**Table 8**

*Comparisons of ERR CABG and ERR THA/TKA Values for Variables*

| | ERR CABG | | | | ERR THA/TKA | | | |
|---|---|---|---|---|---|---|---|---|
| | *M* | *SD* | *Min* | *Max* | *M* | *SD* | *Min* | *Max* |
| Stage 6 | 0.99 | 0.10 | 0.77 | 1.42 | 1.01 | 0.14 | 0.66 | 1.54 |
| Stage 7 | 1.00 | 0.09 | 0.79 | 1.13 | 0.99 | 0.13 | 0.71 | 1.26 |
| Micropolitan | 1.02 | 0.08 | 0.86 | 1.20 | 0.98 | 0.11 | 0.71 | 1.24 |
| Metropolitan | 0.99 | 0.10 | 0.77 | 1.42 | 1.01 | 0.14 | 0.66 | 1.54 |
| 1–399 beds | 1.01 | 0.09 | 0.80 | 1.42 | 1.01 | 0.13 | 0.66 | 1.54 |
| ≥ 400 beds | 0.98 | 0.10 | 0.77 | 1.30 | 1.00 | 0.15 | 0.71 | 1.42 |

**Table 9**

*Characteristics of Hospitals*

| Variable | EMRAM Stage 6 | % | EMRAM Stage 7 | % | Total (*n*) 1,006 | % |
|---|---|---|---|---|---|---|
| ERR CABG | | | | | | |
| 0 (better than average) | 191 | 60.0 | 14 | 45.2 | 205 | 58.6 |
| 1 (worse than average) | 128 | 40.0 | 17 | 54.8 | 145 | 41.4 |
| Total (*n*) | 319 | 100 | 31 | 100 | 350 | 100 |
| ERR THA/TKA | | | | | | |
| 0 (better than average) | 355 | 51.5 | 29 | 51.8 | 384 | 51.5 |
| 1 (worse than average) | 334 | 48.5 | 27 | 48.2 | 361 | 48.5 |
| Total (*n*) | 689 | 100 | 56 | 100 | 745 | 100 |
| EMRAM stage | 931 | 92.5 | 75 | 7.5 | 1,006 | 100 |
| Hospital's location | | | | | | |
| micropolitan | 153 | 20.0 | 6 | 8.0 | 159 | 16.0 |
| metropolitan | 765 | 80.0 | 69 | 92.0 | 834 | 84.0 |
| Total (*n*) | 918 | 100 | 75 | 100 | 993 | 100 |

| Variable | EMRAM Stage 6 | % | EMRAM Stage 7 | % | Total ($n$) 1,006 | % |
|---|---|---|---|---|---|---|
| Number of licensed beds | | | | | | |
| 1–399 | 742 | 80.0 | 52 | 69.3 | 794 | 78.9 |
| ≥ 400 | 189 | 20.0 | 23 | 30.7 | 212 | 21.1 |
| Total ($n$) | 931 | 100 | 75 | 100 | 1006 | 100 |

## Results

### Research Question 1

RQ1: Is there a relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' ERR for CABG or TKA/THA among Medicare patients?

$H_0$1: There is no statistically significant relationship between hospitals’ EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals’ ERR for CABG or TKA/THA among Medicare patients.

$H_a$1: There is a statistically significant relationship between hospitals’ EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals’ ERR for CABG or TKA/THA among Medicare patients.

I used two chi-square tests of independence to determine if a relationship existed between EMRAM stage and CABG ERR and EMRAM stage and THA/TKA ERR. As a result, these are two subhypotheses.

RQ1a: Is there a relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' ERR for CABG among Medicare patients?

*$H_0$*1a: There is not a significant relationship between EMRAM stage and CABG ERR.

*$H_a$*1a: There is a significant relationship between EMRAM stage and CABG ERR. I conducted a chi-square test to assess whether there was a significant relationship between EMRAM stage and CABG ERR, where 1 indicates hospitals with worse than average ERR and a 0 indicates hospitals with better than average ERR. First, the data were determined to meet the chi-square assumptions (see Appendix A). The results were found to be nonsignificant, $\chi^2(1, n = 350) = 2.52$, $p = .112$ (see Table 10). The percentage of hospitals that were at the EMRAM Stage 6 and had an ERR rating of 0 was 60%, which was 1% higher than the hypothesized proportion (59%), while the number of hospitals at the same stage that had an ERR rating of 0 was 40%, which was 1% lower than the hypothesized proportion (41%). The percentage of hospitals at EMRAM Stage 7 that had an ERR rating of 1 was 45%, which was 13% lower than the hypothesized proportion of 58%, while hospitals with ERR rating of 0 was 55%, which was 13% higher than the hypothesized proportion of 42%. Because the p-value ($p = .112$) was greater than my chosen significance level ($\alpha = .05$), I accepted the null hypothesis. The results suggest that there is a not a significant relationship between EMRAM stage and ERR for CABG.

The subhypotheses are as follows for the second part of RQ1:

RQ1b: Is there a relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' ERR for THA/TKA among Medicare patients?

$H_0$1b: There is not a significant relationship between EMRAM stage and THA/TKA ERR.

$H_a$1b: There is a significant relationship between EMRAM stage and THA/TKA ERR.

I conducted a chi-square test to assess whether there was a significant relationship between EMRAM stage and THA/TKA ERR. First, the data were examined, and the data met the chi-square assumptions (see Appendix A). The results were nonsignificant. $\chi^2(1, n = 745) = 0.01$, $p = .970$ (see Table 10). The percentage of hospitals that were EMRAM Stage 6 and had an ERR rating of 0 was 52%, which aligned with the hypothesized proportion of 52%, while the number of hospitals at the same EMRAM stage that had an ERR rating of 1 was 48%, which was also aligned with the hypothesized proportion of 48%. Hospitals that were rated at the EMRAM Stage 7 and had an ERR rating of 0 was 52%, which aligned with the hypothesized proportion of 52%, while the number of hospitals at the same EMRAM stage that had an ERR rating of 1 was 48%, which was aligned with the hypothesized proportion of 48%. Because the p-value ($p = .970$) is greater than my chosen significance level ($\alpha = .05$), I accepted the null hypothesis. The results suggest that there is a not a significant relationship between EMRAM stage and ERR for THA/TKA.

**Table 10**

*Comparisons by ERR*

| | Goodness of fit | | | |
|---|---|---|---|---|
| ERR | *N* | Df | $\chi^2$ | *p* |
| CABG | 350 | 1 | 2.52 | .112 |
| THA/TKA | 745 | 1 | .001 | .970 |

**Research Question 2**

RQ2: Is there a relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' characteristics (hospitals' location or the number of licensed beds)?

$H_0$2: There is no statistically significant relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' characteristics (hospitals' location or the number of licensed beds).

$H_a$2: There is a statistically significant relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' characteristics (hospitals' location or the number of licensed beds).

As a result, these are two subhypotheses.

RQ2a: Is there a relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and hospitals' location?

$H_0$2a: There is not a significant relationship between EMRAM stage and hospital location.

$H_a$2a: There is a significant relationship between EMRAM stage and hospitals' location.

To determine if a significant relationship existed between EMRAM stage and hospitals' location (i.e., micropolitan, metropolitan), I used a chi-square test of independence. First, the data were examined to determine if they met the chi-square assumptions (see Appendix A), which they did. The results were statistically significant: $\chi^2(1, n = 993) = 3.87, p = .049$ (see Table 11). The association was small (Cohen, 1988), Cramer's V = 0.062. The proportion of hospitals that resided in micropolitan areas and were at EMRAM stage 6 was 17%, which was 1% over the hypothesized proportion 16%. The number of micropolitan hospitals at Stage 7 was 8%, which was one-half of the hypothesized proportion of 16%. Hospitals located in metropolitan areas and that were at EMRAM stage 6 was 83%, which was 1% over the hypothesized proportion 84%. The number of metropolitan hospitals at Stage 7 was 92%, which was 8% over the hypothesized proportion of 84%, which suggest that metropolitan hospitals were more likely to have more mature EHR. Because the p-value (p = .049) is less than my chosen significance level ($\alpha = .05$), the null hypothesis is rejected.

The subhypotheses are as follows for the second part of RQ2:

RQ2b: Is there a relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stages 6 or 7 and the hospitals' number of licensed beds?

$H_0$2b: There is not a significant relationship between EMRAM stage and the hospitals' number of licensed beds.

*H*a2b: There is a significant relationship between EMRAM stage and the hospitals' number of licensed beds.

A chi-square test was also used to determine if there was a significant relationship between EMRAM stage and the number of licensed hospital beds grouped as 1-399 and 400 or more. The data were examined to determine if they met the chi-square assumptions (see Appendix A), which they did. The results indicated that there was a statistically significant relationship: $\chi^2(1, n = 1006) = 4.48$, $p = .034$ (see Table 11). The association was small (Cohen, 1988), Cramer's

V = 0.066. Hospitals with fewer than 400 beds at EMRAM Stage 6 were at 80% compared to 79% of the hypothesized proportion. Hospitals with more than 400 beds EMRAM Stage 6 were 20%, which was 1% less than the hypothesized proportion of 21%. At EMRAM Stage 7, hospitals with fewer than 400 beds were at 69%, which was 10% less than the hypothesized proportion of 79%. Hospitals at EMRAM Stage 7 with more than 400 beds were 31%, which was 10% higher than 21% of the hypothesized proportion, which indicates that larger hospitals were more likely to have more mature EHR. Because the p-value (p = .034) is less than my chosen significance level ($\alpha = .05$), the null hypothesis is rejected.

**Table 11**

*Comparisons of Hospital Characteristics*

| Goodness of Fit | *N* | df | $\chi^2$ | *p* |
|---|---|---|---|---|
| Hospital Location | 993 | 1 | 3.87 | .049 |
| Number of Licensed Beds | 1006 | 1 | 4.48 | .034 |

**Research Question 3**

RQ3: Do hospitals' EHR maturity and characteristics (hospitals' location or the number of licensed beds) predict the ERR for CABG or THA/TKA among Medicare patients?

$H_0$3: There is no statistically significant relationship between hospitals' EHR maturity and characteristics (hospitals' location or the number of licensed beds) to predict the ERR for CABG or THA/TKA among Medicare patients.

$H_a$3: There is a statistically significant relationship between hospitals' EHR maturity and characteristics (hospitals' location or the number of licensed beds) to predict the ERR for CABG or THA/TKA among Medicare patients.

To predict both CABG and THA/TKA ERR, which were recoded as binary variables, I used logistic regression analyses to examine the relationship between the ERR for CABG, ERR for THA/TKA, EMRAM Stage 6 or 7, hospitals' location (micropolitan or metropolitan), and the number of licensed beds (1-399 or 400 or more).

For the first analyses of RQ3, the subhypotheses are as follows:

$H_0$3a: There is not a significant relationship between CABG ERR and EMRAM stage, hospitals' location, and the number of licensed beds.

$H_a$3a: There is a significant relationship between CABG ERR and EMRAM stage, hospitals' location, and the number of licensed beds.

After I examined the assumptions of logistic regression (see Appendix A), the first step was to test whether the data fit the specific model. To determine the data fit, a Hosmer and Lemeshow Goodness-of-Fit (Hosmer & Lemeshow, 2000) test was conducted, $\chi^2(3) = .862$, $p = .711$ and the test was not statistically significant. The non-significant result indicates the data is adequate for analysis purposes. Next, I examined the plot of residuals, and the residuals were in a random pattern (see Appendix B, Figure B1), Next, the highest Cook's value was less than 0.08, which suggested no extreme outliers, and the highest variance inflation factor (VIF) statistic for the independent variables was at 1.04, which indicated multicollinearity was not present.

A logistic regression was performed to ascertain the effects of EMRAM stage, hospitals' location, or the number of licensed beds on the hospitals' CABG ERR. The logistic regression model was not statistically significant, $\chi^2(3) = 6.88$, $p = .076$. The model explained approximately 3% (Nagelkerke $R^2$) of the variance in CABG ERR, which is a pseudo R-squared value, and correctly classified 59.7% of the cases. Sensitivity was 16.6%, specificity was 90.2%, positive predicted value was 54.5%, and the negative predictive value was 39.5% (See Table 12). None of the independent variables were significant in predicting the ERR for CABG. As a result, I fail to reject the null hypothesis. The results are presented in Table 13.

**Table 12**

*ERR CABG Classification Table*

| ERR CABG | Worse (1) | Better (0) | Percentage Correct |
|---|---|---|---|
| Worse than Average | 185 | 20 | 90.2 |
| Better than Average | 121 | 24 | 16.6 |
| Overall Percentage | | | 59.7 |

The cut value is .500

**Table 13**

*Variables in the Equation (CABG ERR;* N = *350)*

| Variables | OR | 95% CI Lower | 95% CI Upper | Wald | *p* |
|---|---|---|---|---|---|
| Stages | | | | | |
| Stage 6 | 1.00 | | | | |
| Stage 7 | 1.93 | 0.91 | 4.09 | 2.96 | .085 |
| Hospital Location | | | | | |
| Micropolitan | 1.00 | | | | |
| Metropolitan | 0.80 | 0.27 | 2.38 | 0.16 | .686 |
| Number of Licensed Beds | | | | | |
| 1 – 399 | 1.00 | | | | |
| ≥ 400 | 0.65 | 0.42 | 1.00 | 3.80 | .051 |

$H_0$3b: There is not a significant relationship between THA/TKA ERR and EMRAM stage, hospitals' location, and the number of licensed beds.

$H_a$3b: There is a significant relationship between THA/TKA ERR and EMRAM stage, hospitals' location, and the number of licensed beds.

To determine if the data fit the model, a Hosmer and Lemeshow Goodness-of-Fit (Hosmer & Lemeshow, 2000) test was conducted, $\chi^2(3) = 3.07$, $p = .381$ and the test was not statistically significant, which indicates the data is adequate for analysis purposes. Next, I examined the plot of residuals (see Appendix B, Figure B2), and the residuals were in a random pattern. Additionally, the highest Cook's value was 0.08 and the highest VIF statistic for the independent variables was at 1.07.

A logistic regression was performed to ascertain the effects of EMRAM stage, hospitals' location, and number of licensed beds on the hospitals' THA/TKA ERR. The logistic regression model was statistically significant, $\chi^2(3) = 9.19$, $p = .027$. The model explained approximately 2% (Nagelkerke $R^2$) of the variance in predicting THA/TKA ERR which is a pseudo R-squared value, and correctly classified 54.9% of cases. For this analysis, 51.5% of the cases were classified correctly (See Table 14), and sensitivity was 62.6.%, specificity was 47.7%, positive predicted value was 52.9%, and the negative predictive value was 42.5%. Of the three predictor variables, only one was statistically significant: hospitals' location (see Table 15). Hospitals in metropolitan areas were 1.85 times (*CI*: 1.25 – 2.75) more likely than hospitals in micropolitan areas, in obtaining an ERR of 1 (worse than average) for THA/TKA. EMRAM stage and the number of licensed beds were not significant predictors of ERR for THA/TKA. As a result, $H_0 3$ was rejected, and the alternative hypothesis was accepted. The results are presented in Table 15.

**Table 14**

*ERR THA/TKA Classification Table*

| ERR THA/TKA | Worse (1) | Better (0) | Percentage Correct |
|---|---|---|---|
| Worse than Average | 384 | 0 | 100 |
| Better than Average | 361 | 0 | 0 |
| Overall Percentage | | | 51.5 |

The cut value is .500

**Table 15**

*Variables in the Equation (THA/TKA ERR;* N = *745)*

| Variables | Odds Ratio | 95% CI Lower | 95% CI Upper | Wald | *p* |
|---|---|---|---|---|---|
| Stages | | | | | |
| Stage 6 | 1.00 | | | | |
| Stage 7 | 0.97 | 0.56 | 1.68 | 0.01 | .910 |
| Hospital location | | | | | |
| Micropolitan | 1.00 | | | | |
| Metropolitan | 1.85 | 1.25 | 2.75 | 9.36 | .027 |
| Number of Beds | | | | | |
| 1 - 399 | 1.00 | | | | |
| More than 400 | 0.73 | 0.52 | 1.03 | 3.25 | .071 |

## Summary

The chi-square and logistical regression analyses that I performed as the basis of this study yielded three main findings. First, a chi-square statistical test showed no significant relationship between hospitals' EHR maturity and ERR for CABG or ERR for THA/TKA among Medicare patients. Second, however, a chi-square statistical test showed a significant relationship between hospitals' EHR maturity and hospitals' location ($p$ = .049) and the number of licensed hospital beds ($p$ = .034). Third, logistic regression showed no statistically significant relationship between hospitals' EHR maturity and hospitals' characteristics (location or the number of licensed beds) to predict hospitals' ERR for CABG or THA/TKA among Medicare patients. However, hospitals' location was statistically significant in predicting ERR for THA/TKA ($p$ = .027).

These results demonstrate the impact of hospital characteristics on EHR maturity. The results indicate a relationship between hospitals' location, the number of licensed beds, and EHR maturity. However, it appears that hospitals' investments in mature EHR may not lead to improvements in healthcare quality measures such as reducing excess readmissions among Medicare patients with the procedure-specific conditions of the HRRP. In the next section, I discuss the implications of these results for best practices among hospitals in the United States.

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

The purpose of this quantitative study was to investigate the relationship between hospitals' EHR maturity and excess readmissions. Additionally, I examined whether specific hospital characteristics impacted EHR maturity and if EHR maturity and hospital characteristics were predictors of hospitals' ERR for CABG or THA/TKA. The independent variable was EHR maturity, as measured by the EMRAM stage. The dependent variables included hospitals' ERR for CABG or THA/TKA and hospital characteristics, specifically hospitals' location (micropolitan or metropolitan) and the number of licensed beds (1-399 and over 400). Everett Rogers's (1983) DOI theory was the theoretical framework for this study. This theory explains the characteristics that impact the rate of diffusion or the spread of an innovation (Rogers, 1983). The DOI theory also allows researchers to predict the extent of diffusion of an innovation based on organizational characteristics (Sadoughi et al., 2018).

Since the HITECH Act of 2009, U.S. healthcare providers have invested a significant amount of financial and human resources to adopting HIT, such as the EHR, to improve quality care measures such as reducing excess readmissions. About 90% of hospitals have adopted some version of HIT since 2016 (Atasoy et al., 2019). However, as it relates to the EHR, there is variation in the maturity of the technology adopted by hospitals. These variations in the technologies' capability or maturity make it difficult for researchers to analyze the full impact of the technology on quality measures such as excess readmissions (Kulaylat et al., 2018).

I employed a quantitative method using the chi-square test and logistic regression model for analysis of the variables. The results suggest that no statistically significant relationship exists between hospitals' EHR maturity in hospitals that have achieved Stage 6 or 7 of EMRAM, and hospitals' ERR for CABG or THA/TKA. However, there was a statistically significant relationship between hospitals' EHR maturity in hospitals that have achieved EMRAM Stage 6 or 7 and hospital characteristics, specifically hospitals' location and the number of licensed beds. However, EHR maturity and the number of licensed beds were not predictors of hospital's ERR for CABG or THA/TKA, but EHR maturity and hospital location were significant predictors of hospitals' ERR for THA/TKA.

## Interpretation of the Findings

The results confirmed the null hypothesis that hospitals' adoption of the most advanced form of EHR maturity, EMRAM Stages 6 or 7, did not influence hospitals' ERR for CABG or THA/TKA. This research confirms, in part, the Martin et al. (2018) study, which found no significant relationship between organizational digital maturity and readmission risk. Other researchers have noted that EHR adoption can improve quality care, safety, and healthcare efficiency (Atasoy et al., 2019; Jones et al., 2014). However, the results of this study are in keeping with Martin et al.'s assertion that hospitals' technological maturity may not impact readmissions.

Although there was no relationship between EHR maturity and ERR for the conditions studied, further analysis revealed a significant relationship between EHR maturity and hospital characteristics. Most hospitals that achieved EMRAM Stages 6 or 7 were in metropolitan areas, matching Rogers’s (1983) contention that early adopters of innovation tend to have different socioeconomic characteristics than do late adopters. The results of this study indicate a reduced likelihood that "late-adopter" hospitals might use this research as an impetus to adopt more advanced forms of EHR because excess readmissions of Medicare patients appear to remain the same regardless of EHR maturity. Micropolitan hospitals and smaller hospitals were less likely to have achieved EHR Stage 7, which is an indicator of the speed of the diffusion of new, advanced technology. Rogers's DOI theory suggests that users must conclude that the innovation is better than the previous system (Akça & Özer, 2014). Additionally, the results aligned with the findings of Adler-Milstein et al. (2017), which suggested a relationship between hospital characteristics, such as hospitals' location, the number of licensed beds, and EHR adoption. Adler-Milstein et al. found that hospitals with 400 or more beds were significantly more likely to have adopted advanced EHR functions than were hospitals with fewer than 100 beds ($p < .01$).

Finally, regarding EHR maturity and the number of licensed beds as predictors of ERR for CABG and THA/TKA, no relationship was found. However, EHR maturity and hospitals’ location were predictors of ERR for THA/TKA. Hospitals located in micropolitan areas were more likely than hospitals in metropolitan areas to have better than average ERR for THA/TKA. Based on the findings, hospitals in metropolitan areas were 1.85 times (*CI*: 1.25 – 2.75) more likely than hospitals in micropolitan areas, in obtaining an ERR of 1 (worse than average) for THA/TKA. This result contrasts with the findings of Kurtz et al. (2016), which found that hospital location (urban or rural) had no impact on readmission risk. However, this result demonstrates the impact that EHR maturity can have on healthcare quality, specifically in hospitals in less advantaged areas. This result also confirms the study performed by Lin et al. (2019), which indicates that EHR adoption has the most impact in hospitals in disadvantaged areas.

## Limitations of the Study

The results of this study were limited by the HIMSS database, which only has data on hospitals that have achieved EMRAM Stage 6 and 7. As a result, hospitals at EMRAM Stages 1 to 5 were not considered in this study. Because HIMSS Analytics changed scholars’ ability to access data sets from 2018 forward, this study was restricted to fiscal year 2017 data to correspond with the 2017 CMS data set. Using data from this time frame alone may not provide the most recent information regarding the hospital's current EMRAM stage or the current ERR status of the conditions studied. Additionally, although CMS provides ERR data for the six targeted conditions of the HRRP, I only analyzed the hospitals’ ERR for the procedure-specific conditions CABG and THA/TKA. Because the number of rural hospitals included in the HIMSS data set was limited to seven, this study only included micropolitan (population between 10,000 and 50,000) and metropolitan (population greater than 50,000) hospitals. Because I did not include rural hospitals (population less than 10,000). I could not come to any conclusions about the impact of EHR maturity on ERR in rural hospitals. Additionally, because this was a secondary data set, merging different data sets presented the possibility of missing or incomplete data. Finally, the data's reliability and validity were defined and limited by the available HIMSS and CMS secondary data sets and their process of collection and statistical manipulation of the data.

## Recommendations

According to previous research, EHR adoption could improve healthcare quality and decrease healthcare costs (Kruse & Beane, 2018). Based on the results of this study, however, hospitals may not see any significant reductions in excess readmissions simply by upgrading to mature EHR technology. The results of this study did not provide much insight into EHR maturity and ERR for the procedure specific conditions studied; however, the results suggest a relationship between EHR maturity and hospitals' characteristics (location and the number of licensed beds). It appears more likely that larger hospitals in metropolitan areas will tend to be at higher EHR maturity and have higher ERR than smaller hospitals in micropolitan areas.

Because the results of this study yielded no relationship between hospitals that have achieved EMRAM Stage 6 or EMRAM Stage 7 and hospitals' ERR, it would be difficult to recommend policy changes that could accelerate the adoption of advanced EHR based on this study alone. Stage 6 EMRAM includes the capability of EHR technology to report technology-enabled medication, blood products, human milk administration, risk reporting, and full CDS. In contrast, Stage 7 EMRAM represents an entirely paperless environment where all aspects of patient care, privacy, and disaster recovery are managed electronically (HIMSS Analytics, 2017b). However, it does not appear that these additional functionalities in Stage 7 impact quality metrics such as excess readmissions or ERR.

I recommend future studies with complete data sets, including data from hospitals that have achieved EMRAM Stages 4 to 5 for comparison with EMRAM Stages 6 to 7 to examine if higher stages of EHR maturity result in the quality benefit compared to the financial investments. Furthermore, I would recommend additional research that examines all six targeted conditions of the HRRP to make conclusions about the impact of hospitals' EHR maturity on all ERR that result in hospital penalties among Medicare patients. Finally, because this study was limited to metropolitan and micropolitan hospitals, I recommend that future studies investigate the relationship between EHR maturity and ERR in rural hospitals with a larger data set.

## Implications for Professional Practice and Social Change

The adoption of EHR adoption cost the U.S. healthcare system about $14.5 billion in 2019 and is projected to total $19.9 billion by 2024 (Jercich, 2020). However, Kharrazi et al. (2018) predicted that most US hospitals would not reach the highest EMRAM maturity (Stage 7) until 2035 if no policy or technological changes exist. The results of this study do not suggest that investments in mature EHR maturity (EMRAM Stage 6 or 7) would impact the quality measure of excess readmissions or help to reduce the $17.8 billion spent annually by Medicare on readmissions (CMS, 2018) or decrease the risk of hospitals' financial penalties associated with high ERR for the procedure-specific conditions of the HRRP. As such, hospital administrators may need to invest in other methods to reduce excess readmissions among Medicare patients for those conditions. However, administrators who invested in advanced EHR might find benefits in other quality metrics not included in this study.

Although this study suggests no relationship between EHR maturity and ERR, it shows that hospitals in micropolitan areas with EMRAM Stage 6 or 7 have lower (better than average) ERR for THA/TKA. As a result, investments in EMRAM Stage 6 and 7 in micropolitan hospitals may lower excess readmissions. Based on Rogers's (1983) observations of late adopters of technology, smaller and micropolitan hospitals may be less likely to implement HIT than larger and metropolitan hospitals. Lin et al. (2019) and Haggstrom et al. (2019) also confirmed Rogers's observation by finding that larger hospitals are more likely to invest in technology than smaller hospitals. Therefore, my recommendation for professional practice would be to continue to investigate the benefits of mature EHR in smaller and micropolitan hospitals. Reducing excess readmissions can lead to positive social change in healthcare by supporting the triple aim of healthcare of providing better-quality care, decreasing healthcare costs, and improving patient experiences (Sheikh et al., 2015).

## Conclusion

Researchers have found it difficult to assess the full impact of EHR maturity on quality outcomes such as excess readmissions due to the variation of EHR capability in hospitals. The available literature does not provide much insight on how EHR maturity and hospital characteristics impact ERR for hospitals with Medicare patients or how hospital characteristics affect EHR maturity (van Poelgeest et al., 2017). This study suggests that variations in hospitals’ EHR maturity have no impact on reducing ERR among Medicare patients. However, the results of this study do suggest a relationship between EHR maturity, hospitals’ location, and ERR. Future researchers should consider other methods that may reduce excess readmissions in hospitals with Medicare patients.

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# Appendix A: Assumptions for Research Questions

Two assumptions of the chi-square test of independence for RQ1 and RQ2 were (a) independence of observations, which indicates that each subject gave one response and each observation was a different subject, and (b) at least five responses in each cell. All four analyses for RQ1 and RQ2 met these assumptions.

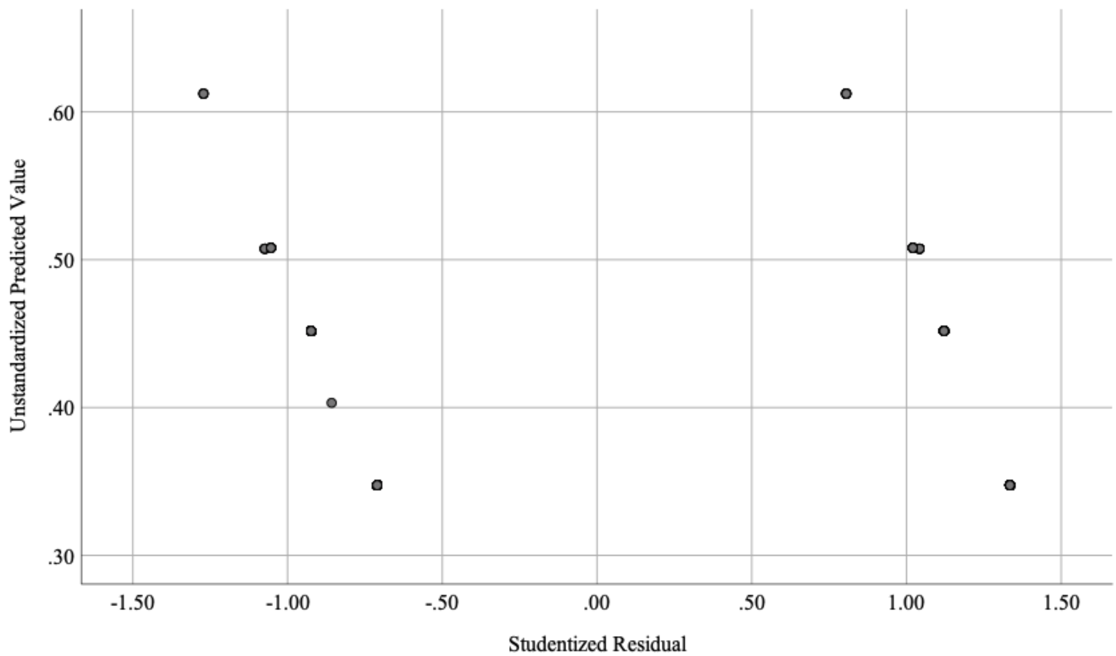
For logistic regression in RQ3, I assumed, first, that the dependent variable was dichotomous and, second, that the observations were independent (DeMaris, 1995). I checked the second assumption by the creating a plot of the residuals and inspecting whether a random pattern, which would indicate independence, was present. The third assumption was that there was no multicollinearity between the independent variables, which was determined by the variance inflation factor, for which the general guideline is that factors exceeding four should be further investigated (DeMaris, 1995). The fourth assumption was that the data did not have extreme outliers, which was assessed by examining Cook's distance for each observation where observations over one may indicate too much influence over the dependent variable (DeMaris, 1995). The fifth assumption was that the sample size was robust (DeMaris, 1995). Finally, I assumed that a linear relationship would be present between the continuous independent variables and the dependent variable (DeMaris, 1995). However, because all the independent variables were categorical, this assumption could be ignored for this research question.

# Appendix B: Regression Analysis

The independent and dependent variables are dichotomous, which is why there are two lines on each scatterplot.

**Figure B1**

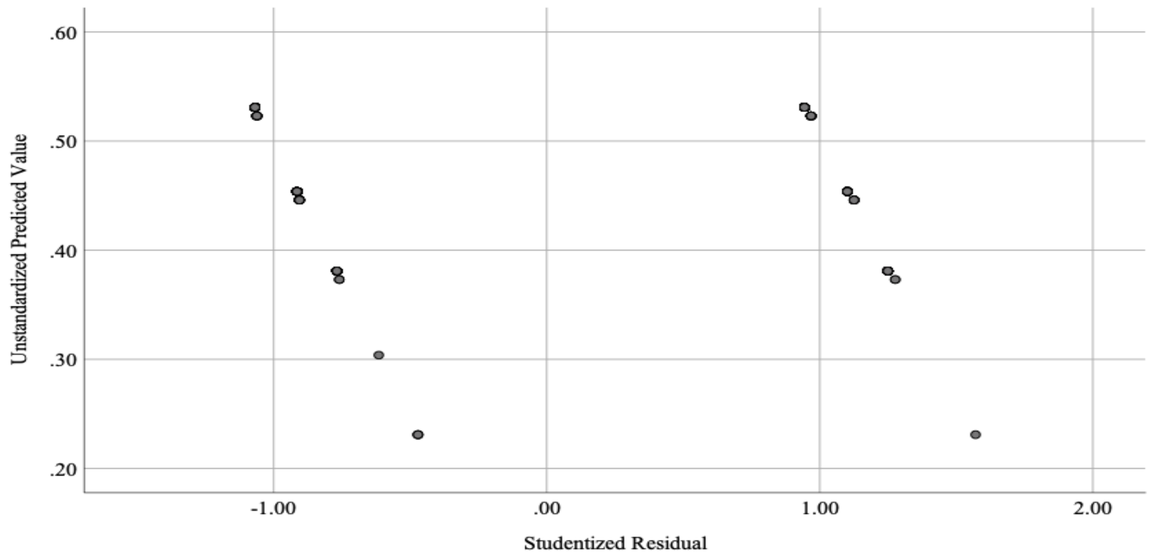
*Scatterplot of the Regression Analysis of Unstandardized Residuals and Studentized Residual Values for CABG ERR*




*Note*. CABG ERR = coronary artery bypass graft excess readmission ratio.

**Figure B2**

*Scatterplot of the Regression Analysis of Unstandardized Residuals and Studentized Residual Values for THA/TKA ERR*




*Note*. THA/TKA ERR = excess readmission ratio for elective primary total hip or total knee arthroplasty.