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BOOST Tool Implementation and Sepsis Readmissions, Length of Stay, and Patient Satisfaction

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Walden University
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Abstract

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by

Jane Venus-Nocentelli

MA, Lewis University, 2007

BSN, Loyola University, 1994

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Health Sciences

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Abstract

Sepsis is a global concern because it contributes to high mortality rates, increased healthcare costs, and poor patient outcomes. Health care organizations have used risk stratification tools such as the Better Outcomes by Optimizing Safe Transitions (BOOST) tool to reduce unnecessary readmissions, decrease length of hospital stays, and improve patient health outcomes. But there is limited data on the use of the BOOST tool in the sepsis population and the impact on readmissions and length of stay. The purpose of this quantitative study was to investigate the relationship between BOOST tool implementation, readmissions, and length of stay in patients with sepsis. Using logistic regression and linear regression, an analysis was conducted to determine the statistical significance between BOOST tool implementation, readmissions, and length of stay. This was a secondary data analysis of 1,394 sepsis inpatients from an acute care hospital in the West Coast region of the United States who met the inclusion criteria. Contrary to expectations, this study indicated an increase in sepsis readmissions and length of stay after BOOST tool implementation. Low BOOST tool completion rates during the COVID-19 pandemic may have impacted the results of this study. However, the best-practice elements listed within the BOOST tool are still applicable for the sepsis population in standardization of the discharge planning process. Application of Gittell's relational coordination model indicated an opportunity to improve the quality of sepsis care coordination. Results of this study may contribute to the implementation of an alternative tool to monitor readmissions and length of stay in the sepsis population.

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Dedication

This doctoral work is dedicated to my loved ones. For my husband and father of my children, Mr. Charles Nocentelli, my soulmate and best friend. Thank you for always supporting my career and educational aspirations. There are no words to express my love and gratitude for taking this arduous journey with me. You were my rock as I battled breast cancer while mourning the loss of my father during the proposal phase of this dissertation. God has gifted me with a good man. Thank you for keeping the household in order so that I could focus on my research study. I owe you many date nights!

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Chapter 1: Introduction to the Study

Sepsis morbidity and mortality is a public health concern that affects many populations globally. Sepsis is a prolonged infection that can be fatal, is often costly, and is associated with long hospital stays, frequent readmissions, and high mortality rates in comparison to other conditions (Hajj et al., 2018). Appropriate care coordination can lead to reduced sepsis readmissions, decreased length of stay, lower mortality rates, and improved patient outcomes. To avoid unnecessary readmissions, successful care coordination includes the following factors: patient access to healthcare services, patient comprehension regarding their care, communication of the patient's care plan among various providers, and prioritization of the patient's healthcare needs (Marzoug, 2018).

In this quantitative study, I investigated the relationship between the implementation of the Better Outcomes by Optimizing Safe Transitions (BOOST) tool and hospital quality outcomes including readmissions, length of stay, and patient satisfaction in patients with sepsis from the index (initial) admission (see Society of Hospital Medicine, 2015). The BOOST tool is a risk stratification tool created by the Society of Hospital Medicine that addresses interventions in multiple domains including medical, physical, and psychosocial determinants to decrease readmissions (Li et al., 2014). There are eight domains in the BOOST tool that are frequent causes for readmissions: problems with medications, psychological factors, principal diagnosis, physical limitations, poor health literacy, patient support, prior hospitalization, and palliative care (Society of Hospital Medicine, 2015). The goals of implementing BOOST at the partner site are to achieve standardization in the delivery of care, address the patient's needs in the BOOST tool before hospital discharge, and decrease readmissions. Implications for potential social change with BOOST tool implementation may lead to outcomes such as (a) improved quality of sepsis care, (b) patient and caregiver empowerment in sepsis self-care and medical regime, (c) decreased mortality rates, (d) positive health outcomes, and (e) increased public policy and insurance mandates in the care of patients with sepsis.

In Chapter 1, I discuss the problem statement, the purpose of the study, the gap in the literature, the research questions (RQs) and the hypotheses. Also included in this chapter are a discussion of the theoretical foundation, the nature of the study, and operational definitions related to the variables. I conclude the first chapter with a discussion of the significance and potential implications for social change related to this quantitative study.

Background

Sepsis is a prolonged infection that can progress to severe sepsis, organ dysfunction, and a life-threatening condition called septic shock (Rhodes et al., 2017; Singer et al., 2016). Sepsis is a leading cause for hospital readmissions, long hospitalizations, high mortality rates, increased burden of healthcare cost, and poor patient outcomes. There was a global estimate of 48.9 million sepsis cases and 11 million sepsis-related deaths in 2017, which contributed to 19.7% of global deaths (Rudd et al., 2020). There are approximately 14 million sepsis survivors annually (Prescott, 2018). The mean cost for a sepsis readmission was $16,852 and the annual cost for a sepsis readmission was greater than $3.5 billion in the United States (Gadre et al., 2019).

Considering the rates of sepsis morbidity and mortality (Rudd et al., 2020), sepsis is a condition that should be closely monitored to prevent poor health outcomes. Therefore, appropriate sepsis care coordination is necessary to reduce readmissions, decrease the length of hospital stays, and improve health outcomes for the sepsis population.

Care coordination is the multidisciplinary approach to quality and standardized delivery of care throughout the healthcare continuum and manifests as patient-centered care provided by various disciplines with the use of resources in a cost-effective manner (Hoffmarcher et al., 2007). This approach consists of guidelines for inpatient admission, evidence-based therapy, patient and family education, psychosocial factors, transitions of care, and follow-up care 7 days after hospital discharge (O'Connor, 2017). There are different types of care coordination such as primary care coordination, acute care coordination, and post-acute long-term care coordination (Marzoug, 2018). Primary care coordination involves a primary registered nurse who develops a care plan with the patient's primary care providers to ensure the patient receives the appropriate healthcare and follow-up services. Acute care coordination includes access to care that begins with patient entry to the emergency department and care coordination interventions provided by the multidisciplinary healthcare team throughout the hospitalization. Post-acute or long-term care coordination are for patients who reside in skilled nursing facilities. A team of physicians, nurses, therapists, case managers, and social workers conduct coordinated care within the skilled nursing facility (Marzoug, 2018). In this quantitative study, I evaluated acute care coordination of the sepsis population in an academic healthcare system.

A major theme in the body of related literature included legislation mandates to decrease unnecessary hospital readmissions. The Centers for Medicare and Medicaid Services (CMS) transitioned from volume-based care to value-based care under the Affordable Care Act in 2010, which concentrated on paying for quality care at a lower cost (Brooks, 2017). The CMS implemented three pay-for-performance programs that measure the quality of care provided by hospitals (Brooks, 2017). The three programs (discussed in detail in Chapter 2) include the Hospital Readmissions Reduction Program (HRRP), the Hospital Value-Based Purchasing Program, and the Hospital-Acquired Condition Reduction Program (Brooks, 2017). The partner site for this quantitative study abides by the regulations under the HRRP, the Hospital Value-Based Purchasing Program, and the Hospital-Acquired Condition Reduction Program to provide quality care, reduce readmissions, decrease length of stays, and improve patient outcomes.

Another major theme in literature is the creation of risk stratification tools to reduce unnecessary hospital readmissions that are costly and result in poor health outcomes. One risk stratification tool is LACE, which is an acronym for length of stay, acuity, comorbidities, and emergency department visits within the last 6 months (Donze et al., 2016). LACE alerts the interdisciplinary team that a high score could mean a potential readmission and robust discharge planning is necessary to prevent readmissions. Another risk stratification tool is the HOSPITAL score, which is an acronym for hemoglobin level, oncology service discharge, sodium level, procedures, index admission type, admissions from the previous year, and length of stay (Donze et al., 2016). Although the LACE and HOSPITAL scores predict unnecessary hospital readmissions, they do not provide specific interventions to guide the multidisciplinary team in ensuring discharge readiness, particularly in domains including social determinants of health. The BOOST tool identifies medical and psychosocial risk factors with the inclusion of interventions to prevent readmissions and poor health outcomes.

Prior to BOOST tool implementation, the partner site for this quantitative study used only the LACE+ tool to predict readmissions; however, this tool does not include interventions such as those listed in the BOOST tool to guide in risk specific interventions to prevent readmissions. Within each domain, the Society of Hospital Medicine (2015) included risk specific interventions within the BOOST tool that serve as a checklist for the multidisciplinary healthcare team to guide in the delivery of care during inpatient admission and after hospital discharge. The eight Ps pose a risk for readmissions if not addressed prior to hospital discharge. The partner site for this quantitative study envisioned that the BOOST tool would allow for standardized delivery of care that would apply best practices in care coordination to reduce readmissions, decrease length of hospital stay, and improve patient outcomes.

Appropriate sepsis care coordination such as those listed in the BOOST tool are necessary for continuity of care to guide in positive health outcomes for sepsis survivors. But there are limited data on BOOST tool implementation and the sepsis population. The purpose of this quantitative study was to investigate the relationship between BOOST tool implementation and hospital quality outcomes including readmissions, length of stay, and patient satisfaction in patients with sepsis.

Problem Statement

In the United States, unnecessary hospital readmissions are concerning due to the rising healthcare costs, which has gained the attention of federal agencies. The annual expenditure for unnecessary hospital readmissions in the United States is $20 billion (Robinson & Hudali, 2017). Unnecessary hospital readmissions are preventable readmissions with earlier access to care and outpatient resources (Klein, 2020). Necessary hospital readmissions, on the other hand, are based on the severity of illness and intensity of hospital service required for a patient to be readmitted (Sederer & Summergrad, 2006). Decreasing unplanned hospital readmissions has become a national healthcare priority supported by the CMS (Robertson, 2017). The CMS began penalizing acute care facilities in 2012 for excessive readmissions within 30 days post discharge, accumulating to approximately $2 billion in penalty fees for hospitals in the United States (Boccuti & Casillas, 2017). To decrease unnecessary hospital readmissions that are costly, attention should focus on standardization of best practices that promote positive health outcomes.

Sepsis is a common readmission diagnosis, yet 40% of sepsis readmissions are preventable (Norman et al., 2017). Sepsis contributes to high mortality rates, increased healthcare cost, unnecessary readmissions, and poor patient outcomes. Patients with sepsis have an increased risk for hospital readmission and mortality as well as longer length of hospital stays compared to patients with other conditions (Hajj et al., 2018). Additionally, the annual cost for a sepsis readmission in 2017 was greater than $3.5 billion in the United States (Gadre et al., 2019). Due to the rapid increase in sepsis-related deaths, and the rise of annual readmission cost, appropriate sepsis care coordination is essential in the prevention of adverse events such as unnecessary readmissions. Coordination of care in preventing unnecessary readmissions includes specific criteria for the following: inpatient admission, evidence-based therapy in the acute care setting, patient and family education, addressing psychosocial factors, transition of care post-hospital discharge, and access to follow-up care within 7 days after hospitalization (O'Connor, 2017).

There is limited literature on readmissions, average length of stay, and patient satisfaction in patients with sepsis before and after BOOST implementation. Previous researchers investigated the eight variables in the BOOST tool, finding a 2% hospital readmission reduction and a length of stay decrease by 0.5 days after BOOST implementation in medical-surgical units (Hansen et al., 2013), and the tool helped predict readmissions based on the listed risk factors (Lee et al., 2016; Sieck et al., 2019). But other researchers did not find a statistically significant relationship in length of stay and BOOST tool when applied to inpatient mobility on a general medicine unit (Johnson et al., 2021). These studies, however, did not include readmissions, length of stay, and patient satisfaction in patients with sepsis. Additionally, none of these studies evaluated patient satisfaction with discharge elements from the BOOST tool. I addressed the gap in literature by comparing before and after BOOST implementation and the relationship to readmissions and length of stay. I was unable to conduct hypothesis testing from the Press Ganey patient satisfaction surveys; therefore, I was unable to draw a conclusion on patient satisfaction with the BOOST elements. The sample was obtained from the inpatient hospital records of an academic healthcare system in the West Coast region of the United States. If a readmission for sepsis occurred within 30 days after a hospital discharge, it was classified as a readmission.

Purpose

The purpose of this quantitative study was to investigate the relationship between BOOST tool implementation and hospital outcomes such as readmissions, length of stay, and patient satisfaction in patients with sepsis by comparing before and after BOOST implementation and the relationship to those outcomes. The independent variable was BOOST tool implementation. The dependent variables were readmissions and index (initial) admission length of stay. The control variables were age, gender, health insurance coverage, and disease state (sepsis, severe sepsis, septic shock). I compared before and after BOOST data to determine whether readmissions and length of stay decreased after BOOST implementation. Interventions outlined by the Society of Hospital Medicine (2015) in the BOOST tool kit may guide in the transitions of care and community resource linkage post discharge from the hospital. An analysis of the BOOST tool implementation may identify best practices in value-based care across the healthcare continuum.

Research Questions and Hypotheses

RQ 1: What is the relationship between BOOST tool implementation and the likelihood of hospital readmissions for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state?

*H_0*1: There is no statistically significant relationship between BOOST tool implementation and the likelihood of hospital readmissions for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state.

*H_a*1: There is a statistically significant relationship between BOOST tool implementation and the likelihood of hospital readmissions for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state.

RQ 2: What is the relationship between BOOST tool implementation and average length of stay for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state?

*H_0*2: There is no statistically significant relationship between BOOST tool implementation and average length of stay for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state.

*H_a*2: There is a statistically significant relationship between BOOST tool implementation and average length of stay for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state.

RQ 3: What is the relationship between BOOST tool implementation and patient satisfaction scores for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state?

*H_0*3: There is no statistically significant relationship between BOOST tool implementation and patient satisfaction scores for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state.

H_a3: There is a statistically significant relationship between BOOST tool implementation and patient satisfaction scores for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state.

Theoretical Foundation

The theoretical foundation for this study was the relational coordination theory. The foundation of relational coordination theory stemmed from organizational theory and applied in healthcare interdisciplinary practice (Daniel et al., 2017). In 1999, Gittell (2000) coined the concept of relational coordination through her work in flight departure efficiency. In another study, Gittell et al. found that the application of relational coordination improved delivery of care, patient outcomes, and decreased length of stay. Relational coordination theory identifies key concepts in care coordination that include team structure, knowledge and technology, need for coordination, administrative and operational processes, exchange of information/communication, goals, roles, quality of relationship, patient outcome, and organizational or inter-organizational outcome (Van Houdt et al., 2013).

The relational coordination theory was appropriate for this quantitative study for several reasons. By applying relational coordination theory to the domains in the BOOST tool, it may be possible to (a) standardize practices in discharge preparation, (b) educate and empower patients and caregivers in self-care, (c) improve health literacy in disease management and prevention to promote health and well-being, (d) decrease unnecessary hospital readmissions, and (e) improve quality of life. The concepts of relational coordination allow for the provision of prompt quality care, reduction of duplicative efforts through effective team communication, and cost-effective use of resources. The model of relational coordination was applied to the RQs of this study. In RQ 1, the assessment of the relationship between BOOST tool implementation and readmissions occurred, where the BOOST tool fell under the relational coordination category and readmissions fell under quality in the performance category of the relational coordination model. In RQ 2, an assessment of the relationship between BOOST tool implementation and length of stay occurred, where the BOOST tool fell under the relational coordination category and length of stay fell under quality in the performance category of the relational coordination model. Additional details on relational coordination theory and model illustration are provided in Chapter 2.

Nature of the Study

The nature of this study was a quantitative analysis with the use of multiple logistic regression and multiple linear regression. The sample of secondary de-identified data came from the medical records of hospitalized patients discharged from an academic healthcare system in the West Coast region of the United States. The index (initial) admission and readmission diagnosis of sepsis, severe sepsis, or septic shock were the inclusion criteria. An admission was considered a readmission if it occurred within 30 days of the hospital discharge. The years January 2017–June 2019 are before BOOST implementation period and the years July 2019–April 2021 are after BOOST implementation period, which was used to assess statistical significance before and after BOOST tool implementation, readmissions, and length of stay in the sepsis population. The independent variable was BOOST tool implementation. The dependent variables were readmissions and length of stay. The control variables were age, gender, health insurance coverage, and disease state.

I utilized multiple logistic regression and multiple linear regression to investigate RQ 1 and RQ 2. Multiple logistic regression was used to determine the presence, strength, and direction of the relationship between BOOST tool implementation and readmissions in patients with a sepsis diagnosis. Multiple linear regression was used to assess the relationship between BOOST tool and average length of stay from the index (initial) admission in patients with sepsis. I initially proposed to use multiple linear regression to evaluate the relationship between BOOST tool implementation and patient satisfaction with discharge information provided for sepsis patients. However, due to lack of access at the respondent level for the patient satisfaction surveys, a simple descriptive analysis without significance testing was used instead.

Operational Definitions

Better Outcomes by Optimizing Safe Transitions (BOOST): The BOOST tool was created by the Society of Hospital Medicine (2015) to provide risk stratification interventions in readmission reduction related to problems with medications, psychological factors, principal diagnosis, physical limitations, poor health literacy, patient support, prior hospitalization, and palliative care. In this quantitative study, BOOST tool implementation was the independent variable.

Care coordination: Care coordination is the patient-centered care provided by various disciplines with the utilization of resources in a cost-effective manner (Hoffmarcher et al., 2007). Care coordination involves a standardized delivery of quality care throughout the healthcare continuum. There are three types of care coordination: primary care coordination, acute care coordination, and post-acute or long-term care coordination (Marzoug, 2018). For this quantitative study, acute care coordination was examined.

Length of stay: The number of days from the hospital admission date to the hospital discharge date (Baek et al., 2018). For this quantitative study, the index (initial) admission length of stay was examined.

Patient satisfaction: The patient experience before, during, and after a hospitalization, which is related to the quality of care provided (Berkowitz, 2016). For this quantitative study, patient satisfaction scores were reviewed from the Press Ganey aggregated data after hospital discharge.

Readmissions: A readmission is defined as a hospital readmit after an initial hospitalization (CMS, 2020b). For this quantitative study, readmissions that occurred within 30 days after a hospital discharge were examined.

Sepsis: Sepsis is a severe infection associated with organ dysfunction (Cohen et al., 2015). For this quantitative study, sepsis is a disease state variable, an inclusion criterion, and a categorical variable. As an indicator of severity, sepsis can be an ordinal variable.

Severe sepsis: Severe sepsis is associated with the severity of organ dysfunction (Angus & van der Poll, 2013). For this quantitative study, severe sepsis is a disease state variable, an inclusion criterion, and a categorical variable. As an indicator of severity, severe sepsis can be an ordinal variable.

Septic shock: Sepsis and severe sepsis can lead to a life-threatening condition called septic shock (Rhodes et al., 2017). Physiological factors such as hypotension, thrombosis, and decreased oxygen levels in the setting of organ dysfunction contribute to septic shock (Angus & van der Poll, 2013). For this quantitative study, septic shock is a disease state variable, an inclusion criterion, and a categorical variable. As an indicator of severity, septic shock can be an ordinal variable.

Assumptions

There are four assumptions related to this study. The first assumption was that the secondary data retrieved from the electronic health records of an academic healthcare system were accurate. The second assumption was that the BOOST tool was properly uploaded in the patients' charts. The third assumption was that each designated discipline appropriately documented on their assigned *P* prior to hospital discharge. The fourth assumption was that patients provided honest feedback in the patient satisfaction surveys regarding care coordination and discharge planning. It was essential to consider these assumptions for this quantitative study because inaccurate assumptions can impact the conclusions of this study.

Scope and Delimitations

The scope of this study focused on one academic healthcare institution in the West Coast region of the United States and its use of the BOOST tool in the sepsis population. Since its inception at the partner site in July 2019, the BOOST tool has been electronically implemented in all inpatient charts. The BOOST tool provides a checklist of best practices for standardization and improved quality of practice within the multidisciplinary healthcare team. The participants of this study included adult patients 18 years old and older who have been hospitalized and readmitted with the diagnosis of sepsis, severe sepsis, or septic shock within 30 days of hospital discharge. Secondary data were collected and analyzed to determine the relationship between the BOOST tool implementation, readmissions, and length of stay in patients with sepsis.

The factors that threatened internal validity in this study included confounding elements and statistical regression. For this quantitative study, confounding elements included inconsistencies in documentation within the medical records. Inconsistencies in documentation can lead to miscommunication and unaddressed needs indicated within the BOOST tool. Statistical regression occurred in this study due to the lack of access at the respondent level for the patient satisfaction surveys. I purposefully selected inpatient medical records of patients with sepsis, severe sepsis, and septic shock. By ensuring that the selected sample represented the population, internal validity can be improved.

The use of inclusion and exclusion criteria may improve the external validity of this study. This type of validity indicates the ability of the findings to be generalized to the population at large. This study occurred at one academic healthcare institution in the West Coast region of the United States. This focus on one institution and geographic location poses concerns for generalizability to the sepsis population at large.

Limitations

There were several limitations in this quantitative study. The limitations included low generalizability, confounding factors such as inconsistencies in practice on BOOST tool documentation, and lack of access at the respondent level for the patient satisfaction surveys during data collection. Reasonable measures to address errors related to data extraction included data clean up with the assistance of the informatics and analytics team at the partner site.

The scope of this study included only one academic healthcare institution in the West Coast region of the United States. Archival data were extracted from January 2017 to June 2019 before BOOST implementation and then from July 2019 to April 2021 after BOOST implementation. July 2019 was the inception date for the BOOST tool at the partner site. A reasonable measure to address appropriate sample size was to include all patients with an index (initial) and readmission diagnosis of sepsis, severe sepsis, or septic shock.

Methodological weaknesses included confounding factors such as inconsistencies in practice with providing adequate documentation of the BOOST elements prior to patient discharge from the hospital. Additional confounding factors included patients who have expired, patients who left the hospital against medical advice, and patients who were not readmitted to the partner site for this study. Patients who have expired or left against medical advice were still included in the study if they had a record of a 30-day sepsis readmission after a hospital discharge, which was a reasonable measure to address this limitation.

A potential source of bias is that I am employed at the partner site for this quantitative study. However, I collaborated with the analytics and informatics team during the data collection process to abide by the extraction guidelines from the partner site. Additionally, the analytics and informatics team extracted the data requested for this study.

Significance

Through this quantitative study, I addressed a gap in the literature by evaluating the relationship between BOOST tool implementation, readmissions, and length of stay in patients with sepsis. To answer RQ 1, BOOST tool implementation and readmissions were analyzed to determine whether BOOST implementation reduced readmissions in the sepsis population. To address RQ 2, I investigated BOOST tool implementation and length of stay to determine whether BOOST tool implementation decreased index (initial) length of stay in the sepsis population. I was unable to test the hypothesis in RQ 3. Instead, I conducted a simple descriptive analysis without significance testing on the Press Ganey patient satisfaction scores.

The results of this study may contribute to positive social change through the optimization of sepsis care coordination and discharge planning in patients who may be at high risk for unnecessary hospital readmissions. Additionally, the findings of this quantitative study may provide practical application for clinicians, lawmakers, and insurance payors by implementing best practices in care coordination and reimbursement guidelines for patients with sepsis. Further, evidence-based practice listed in the BOOST tool such as patient and caregiver education could lead to the following positive outcomes: (a) compliance with sepsis medical regime, (b) empowerment in appropriate sepsis self-care, and (c) improved quality of life in the sepsis population.

Summary

Sepsis has contributed to high mortality rates, increased healthcare burden of cost, and poor patient outcomes. But sepsis readmissions are preventable through the application of best practices in care coordination. The BOOST tool includes risk interventions that address the eight common factors in patients returning to the hospital. Multiple logistic regression and multiple linear regression were used to investigate BOOST tool implementation and its relationship to the RQs of this quantitative study, focusing on the relationship between BOOST tool implementation and hospital readmissions as well as length of stay.

Chapter 2 includes a review of evidence-based literature on variables including care coordination, sepsis, readmissions, length of stay, patient satisfaction, and the variables included within the BOOST tool. A literature review on relational coordination theory and legislation mandates pertaining to hospital readmission reduction is also presented, including a synthesis of findings and an identification of remaining gaps. I conclude Chapter 2 with a summary of the purpose of this study and the major themes in literature surrounding the implications of BOOST tool interventions.

Chapter 2: Literature Review

Sepsis is a frequent cause for readmissions, higher length of hospital stays, increased healthcare costs, and high mortality rates. This life-threatening condition occurs due to a prolonged infection that attacks the tissues and organs (Singer et al., 2016). There was a global estimate of 48.9 million sepsis cases and 11 million sepsis-related deaths in 2017 (Rudd et al., 2020). Further, the annual cost for a sepsis readmission in 2017 was greater than $3.5 billion in the United States (Gadre et al., 2019). However, 40% of sepsis readmissions are preventable (Norman et al., 2017). Under the Affordable Care Act in 2012, the HRRP penalized hospitals with excessive readmissions within 30 days post-discharge (Mcllvennan et al., 2015). Appropriate care coordination as outlined in the BOOST tool may identify best practices in the prevention of unnecessary sepsis readmissions. Each of the eight domains outlined in the BOOST tool have interventions that serve as a checklist to guide the multidisciplinary team in delivery of care and prevention of unnecessary readmissions. Although key empirical studies have addressed readmissions, length of stay, and patient satisfaction in sepsis survivors (Huang et al., 2016; McCoy & Das, 2017; Prescott & Angus, 2018; Taylor et al., 2019), these prior studies did not consider the BOOST tool.

The next sections of Chapter 2 include the literature search strategy and theoretical foundation. These are followed by the literature review related to sepsis, readmissions, length of stay, patient satisfaction, and the BOOST tool. Chapter 2 includes an overview of implications for practice, a detailed review of the eight Ps within the BOOST tool, and gaps in prior studies. I conclude this chapter with a summary of the major themes in literature including the connection between the RQs and the framework for this quantitative study.

Literature Search Strategy

The databases I used to facilitate this review included Google Scholar, Thoreau Multi-Database Search, MEDLINE with Full Text, SAGE Journals, and ScienceDirect. The publication dates evaluated for this literature search included peer-reviewed scholarly journal sources from 2017 to 2021. The search range included seminal sources prior to 2017 based on relevance to the subject matter. The keywords used in the search included *sepsis, hospital readmission reduction program, coordination of care, average length of stay, patient satisfaction,* and *BOOST tool. Sepsis* produced 2.3 million results from Google Scholar. *Sepsis readmissions* yielded 189 results from the Thoreau Multi-Database Search. *Hospital readmission reduction program* produced 1,354 results from SAGE Journals. *BOOST (Better Outcomes by Optimizing Safe Transitions)* prompted 17,300 results from Google Scholar. *Coordination of care* revealed 27,852 results from ScienceDirect. *Average length of stay* generated 346 results from MEDLINE with Full Text. *Patient satisfaction with care coordination* displayed 134 results from the Thoreau Multi-Database search. *Relational coordination theory* triggered 74 results from the Thoreau Multi-Database Search.

Theoretical Foundation

Relational coordination theory was the framework used for this study. This theory stemmed from organizational theory and is applied in healthcare interdisciplinary practice (Daniel et al., 2017). In 1999, Gittell (2000) coined the concept of relational coordination through her study on the quality of flight departures. The principles of coordination produce positive outcomes for internal and external customers (Follett, 1949, as cited in Gittell, 2015). In another study, Gittell et al. found that the application of relational coordination improved delivery of care, patient outcomes, and decreased length of stay for patients who underwent total knee and hip arthroplasty.

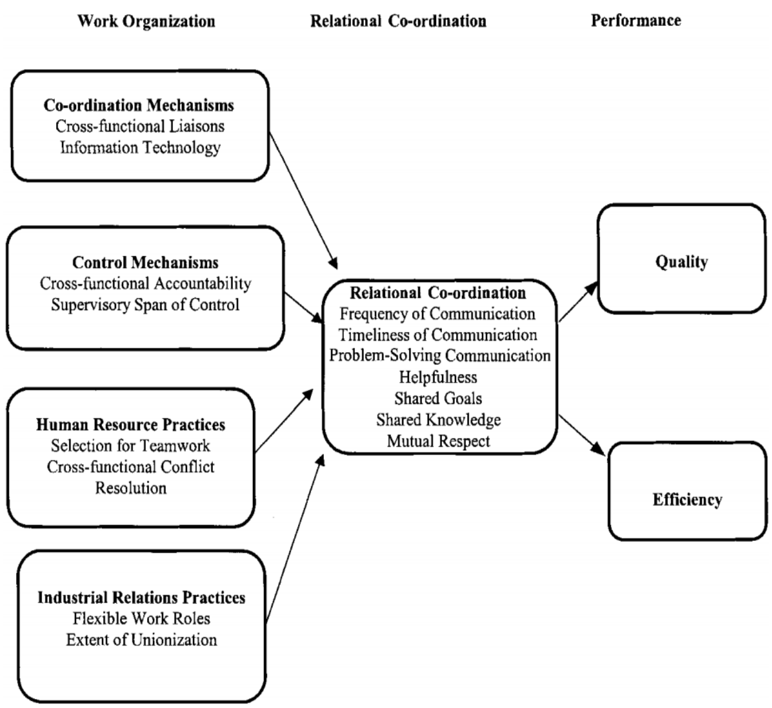
Prior researchers have evaluated the relationship between relational coordination and care coordination. The relationship between care coordination and relational coordination theory includes concepts related to team structure, knowledge and technology, administrative and operational processes, exchange of information and communication, goals, roles, quality of relationship, patient outcomes, and organizational or inter-organizational outcomes (Van Houdt et al., 2013). Hustoft et al. (2018) found a significant relationship between relational coordination team communication and patient scores in activities of daily living ($p = .024$). Similarly, Rundall et al. (2016) reported that clinical leaders were able to identify relational coordination dimensions essential to care management, including standardization of care, coordination of care, patient engagement, and prompt communication. Further, Ghaffari et al. (2020) reported a positive quality of interaction between patients, community providers, and care coordinators. Care coordinators perceived patients benefitted from relational coordination ($p = .003$). Patients perceived care coordinators had a positive influence on managing the patients' health conditions ($p = .01$). Community providers perceived an increasing need for care coordinators ($p = .02$). Relational coordination thus provides a conceptual framework for care coordination as the dynamics of interdisciplinary functioning and communication.

Shared goals allow for frequent team communication fostering relationship building and team collaboration. An engaged team could affect overall organizational performance.

The dynamics of Gittell’s (2000) relational coordination model (see Figure 1) begin with work organization that progresses to relational coordination, which affects overall organizational performance and outcomes. The three categories in Gittell’s model are: (a) work organization, (b) relational coordination, and (c) performance. The first category in the model is work organization, with subcategories including coordination mechanisms, control mechanisms, human resource practices, and industrial relations practices. The second category is relational coordination, with subcategories including frequency, timeliness, and problem-solving communication, helpfulness, shared goals, shared knowledge, and mutual respect. The third is performance, with subcategories including quality and efficiency. The category of relational coordination is applicable to this quantitative study because it includes the subcategories of team communication and shared goals. BOOST tool interventions provide best practices in effective team communication and shared goals. Effective team communication could lead to team collaboration and improve overall performance related to readmissions, length of stay, and patient experience. Relational coordination theory was the best choice for this quantitative study because the concepts of this theory may enable practitioners to standardize interdisciplinary practices that produce positive patient outcomes in patients with sepsis.

Figure 1

Model of Relational Coordination



Note. From "Organizing Work to Support Relational Co-Ordination," by J. H. Gittell, 2000, *International Journal of Human Resource Management*, *11*(3), p. 519. Reprinted with permission from Jody Hoffer Gittell.

The application of relational coordination to this quantitative study was used as a guide in answering the RQs pertaining to BOOST tool implementation, readmissions, and length of stay. In RQ 1, the assessment of the relationship between BOOST tool implementation and readmissions occurred, where the BOOST tool fell under the relational coordination category and readmissions fell under quality in the performance category of the relational coordination model. In RQ 2, an assessment of the relationship between BOOST tool implementation and length of stay occurred, where the BOOST tool fell under the relational coordination category and length of stay fell under quality in the performance category of the relational coordination model.

Literature Review Related to Key Variables and Concepts

Sepsis Overview

Sepsis is a severe infection linked to frequent hospital readmissions, high length of stays, and high global mortality rates. This condition can lead to a life-threatening complication called septic shock (Rhodes et al., 2017). Sepsis and septic shock affect millions of people world-wide and early intervention is crucial in preventing the potential for mortality in critically ill patients (Rhodes et al., 2017). There was a global estimate of 48.9 million sepsis cases and 11 million sepsis-related deaths in 2017 (Rudd et al., 2020). Fourteen million people survive sepsis annually (Prescott, 2018), but sepsis survivors are at elevated risk for long-term mortality (Shankar-Hari et al., 2019), as they frequently experience cognitive and functional impairments following a sepsis hospitalization (Prescott, 2018). Therefore, close surveillance is essential to monitor infection control practices and disease management to prevent unnecessary hospital readmissions.

Sepsis and Readmission Reduction

Sepsis is a condition that is related to frequent readmissions that lead to increased healthcare cost. Researchers have found a 23.4% readmission rate within 30 days post sepsis discharge (Sun et al., 2016) in addition to 68.6% of sepsis readmissions being from the same infection source (DeMerle et al., 2017). Further, sepsis readmissions occurred in 51.6% of patients who died with infection as the primary source (Dietz et al., 2017). Additionally, the average mean cost for a sepsis readmission was $10,070, which was higher than the mean cost per readmission for chronic obstructive pulmonary disease (COPD) at $8,417, congestive heart failure at $9,051, acute myocardial infarction at $9,424, and pneumonia at $9,533 (Mayr et al., 2017). Proper follow-up care of patients after a hospitalization for sepsis is crucial in prevention of unnecessary hospital readmissions that lead to rising healthcare costs (Singh et al., 2019). Therefore, it is essential to consider variations in sepsis care coordination practices that may pose a readmission risk.

Variations in sepsis readmission rates indicate that there may be inconsistencies in sepsis care coordination practices (Norman et al., 2017). Sepsis readmission rates in the northeast United States were 30.4%, 29.6% in the South, 28.8% in the Midwest, and 27.7% in the West. Additionally, the readmission rate for the partner site is 20%. Therefore, the average range of readmission rates across the United States is 20% to 30.4%, which is a significant difference. Demographic and structural factors with variations in care coordination practices lead to sepsis readmissions (Norman et al., 2017), which show the need to strengthen the standardization in sepsis care coordination. Patients have also expressed concerns related to the standardization of sepsis care coordination (Huang et al., 2016). Variances in practices compromise the efficiency and the quality in the delivery of care. The implementation of the BOOST tool may be a practical option to standardization in care coordination for patients with sepsis. The risk interventions listed by the Society of Hospital Medicine (2015) within the BOOST tool provide evidence-based practices for clinicians across the healthcare continuum to guide in positive patient health outcomes for sepsis survivors.

Implications for Practice

Under the Affordable Care Act in 2010, the CMS transitioned from paying for volume to paying for value (quality of care) that hospitals provide at a lower cost (Brooks, 2017). The CMS implemented three pay-for-performance programs that measure the quality of care that acute care hospitals provide (Brooks, 2017). These programs are the HRRP, the Hospital Value-Based Purchasing Program, and the Hospital-Acquired Condition Reduction Program (Brooks, 2017). The partner site for this quantitative study implemented the BOOST tool to provide quality of care based on federal guidelines under the HRRP, the Hospital Value-Based Purchasing Program, and the Hospital-Acquired Condition Reduction Program.

HRRP

In 2012, the HRRP was created under the Affordable Care Act to monitor excessive hospital readmissions 30 days post discharge because of the rise in healthcare costs (CMS, 2020b). The HRRP continues to monitor targeted conditions for unnecessary hospital readmissions, including acute myocardial infarction, COPD, congestive heart failure, pneumonia, coronary artery bypass graft, elective total hip arthroplasty, and total knee arthroplasty (CMS, 2020b). Based on this monitoring, from 2007 to 2015, 3,387 hospitals in the United States showed readmission rates declined from 21.5% to 17.8% for targeted conditions (Zuckerman et al., 2016). For non-targeted conditions, readmission rates declined from 15.3% to 13.1%. Similarly, 3,395 acute care hospitals showed a decrease in readmissions between the years 2013 to 2015, related to the potential penalties under the HRRP (Lu et al., 2016). However, sepsis is not included as a targeted condition to be monitored.

Previous researchers have supported the inclusion of sepsis as a targeted condition under the HRRP to help address mortality rates, infection control practices, and standardization of sepsis care (Dietz et al., 2017) as well as length of stay and hospital costs (Mayr et al., 2017). When the CMS sepsis criteria was used, national sepsis readmission rate was 12.2%, with an estimated mean length of stay at 7.4 days and an estimated mean cost per readmission at $10,070 (Mayr et al., 2017). In comparison, acute myocardial infarction readmission rate was 1.2% with an estimated mean length of stay at 5.7 days and an estimated mean cost per readmission at $9,424; congestive heart failure readmission rate was 6.7%, with an estimated mean length of stay at 6.4 days and an estimated mean cost per readmission at $9,051; pneumonia readmission rate was 5.2%, with an estimated mean length of stay at 6.7 days and an estimated mean cost per readmission at $9,533; and COPD readmission rate was 4.6%, with an estimated mean length of stay at 6.0 days and an estimated mean cost per readmission at $8,417. The partner site for this quantitative study uses the BOOST tool to decrease readmission rates for targeted and non-targeted conditions, which abides by the conditions regulated by the HRRP guidelines. Although sepsis is not a targeted condition listed in the BOOST tool, the partner site modified the BOOST tool to include sepsis.

Hospital Value-Based Purchasing Program

The paradigm for patient care has shifted from volume-based care to value-based care. The basis for value is on quality care provided and health outcomes in relationship to the necessary cost of care (Chee et al., 2016). In 2012, the CMS implemented the Hospital Value Based Purchasing Program, which measures the hospital quality of care and efficiency (CMS, 2020c). Outcome measures include mortality and complications, healthcare-associated infections, patient safety, patient experience, process, efficiency, and cost reduction. The program allows for incentive payments for hospitals based on performance compared to other hospitals and improvements on performance from a prior period.

Prior researchers evaluated cost efficiency and outcome measures in hospitals that participated in the Hospital Value Based Purchasing Program. Izon and Pardini (2018) considered the relationship between cost inefficiency and participation with the Hospital Value Based Purchasing Program and found that the participating community hospitals in the state of California between 2012 to 2015 were cost-inefficient. Further, Izon and Pardini cited that increased operating costs resulted in high quality scores for conditions including acute myocardial infarction, pneumonia, and heart failure. Organizational goals reflect quality care that involves creating consistency to decrease healthcare cost, enhancing the patient experience, and improving patient outcomes.

Hospital-Acquired Condition Reduction Program

Hospital-acquired infections can pose adverse outcomes for patients. Hospital-acquired conditions occur in the hospital setting such as infections that develop while in the hospital, which can be costly, pose negative health outcomes, and increase length of hospital stay (Brooks, 2017). The CMS implemented the Hospital-Acquired Condition Reduction Program to reduce hospital acquired conditions (CMS, 2020a).

Hospitals in the United States received penalties for hospital-acquired conditions. Brooks (2017) showed that penalty rates in U.S. hospitals from 2015 to 2017 were at $330 million to $430 million at a 1% penalty rate by the CMS. Additionally, Sankaran et al. (2019) found that university affiliated hospitals ($p < .001$) were commonly penalized as patients in these hospitals often acquired hospital related conditions possibly due to longer length of stays. Further, Sankaran et al. did not identify clinical improvements in hospitals receiving penalties. Special procedures for infection control have been implemented in hospitals to prevent adverse outcomes such as sepsis related to hospital-acquired conditions.

Risk Stratification Tools in Readmission Reduction

The creation of risk stratification tools such as the LACE, HOSPITAL, and BOOST were to predict unnecessary hospital readmissions. LACE is the acronym for Length of stay, Acuity, Comorbidities, and Emergency Department visits within the last 6 months (Wang et al., 2014). The LACE tool is a common tool used in the United States to predict hospital readmissions or death within 30 days post-discharge (Wang et al., 2014). The HOSPITAL score investigates multiple factors prior to discharge to identify high risk patients for readmission (Donze et al., 2016). The BOOST tool shows risk factors, which are the primary reasons for readmission. The BOOST tool includes interventions attached to each risk factor to prevent a readmission.

Garrison et al. (2016) and Robinson and Hudali (2017) conducted comparison studies between the LACE, LACE+, and HOSPITAL scores to evaluate performance indicators and reliability in the prediction of 30-day readmissions. Garrison et al. did not find any statistically significant difference in performance indicators. Additionally, prediction of 30-day readmissions were similar between the LACE, LACE+, and HOSPITAL score tools. In contrast, Robinson and Hudali found that the HOSPITAL score provided a higher reliability in the prediction of 30-day readmissions compared to the LACE+ score. Although the LACE+ score and the HOSPITAL score are useful to predict readmissions, they do not include interventions that address the medical and psychosocial determinants that prevent unnecessary readmissions. The BOOST tool, on the other hand, shows the eight common risk factors (i.e., the 8Ps) attached to interventions to prevent a readmission.

LACE

The LACE index tool was derived from a study conducted by van Walraven et al. (2010). The variables analyzed included length of stay, acuity, comorbidities, and emergency department visits to predict readmissions and death within 30 days post-discharge (van Walraven et al., 2010). The LACE tool allows the interdisciplinary healthcare team to identify the patients at highest risk for poor outcomes and to apply post-discharge interventions (van Walraven et al., 2010). The normal range for the LACE score was originally 0 to 19, and scores greater than 19 indicated a high potential for readmission (van Walraven et al., 2010).

In 2012, van Walraven et al. extended the LACE tool to include more variables to predict readmissions or early death. The LACE tool became the LACE+ tool. The plus in LACE+ included additional variables such as age, gender, teaching status of the hospital, diagnoses, number of days on alternate level of care, and elective and urgent hospital admissions (van Walraven et al., 2012). The LACE+ tool is commonly used due to its simplicity (Miller et al., 2018). The LACE+ tool however, does not include interventions such as those listed in the BOOST tool, to prevent a potential unnecessary readmission.

HOSPITAL Score

Previous researchers utilized the HOSPITAL score as a prediction model in readmissions. Donze et al. (2016) implemented the HOSPITAL score to create a prediction model that identified low-risk versus high-risk patients to avoid readmissions and to calculate predictors prior to discharge. Donze et al. found that the HOSPITAL score indicated accuracy ($p < .001$) in the identification of high-risk patients for potential 30-day readmissions post hospital discharge. Likewise, Robinson (2016) discovered the HOSPITAL score to be an accurate predictor of readmissions ($p < .001$). Similarly, Burke et al. (2017) indicated the HOSPITAL score to be reliable and accurate ($p = .77$) in predicting readmissions for conditions under the HRRP. Prediction models such as the HOSPITAL score are useful in identifying patients who may be at high risk for readmissions. However, the predictors for readmission in the HOSPITAL score do not include determinants of health such as psychosocial components. The predictors in the HOSPITAL score are limited to the Hemoglobin level, Oncology service discharge, Sodium level, Procedures, Index admission Type, Admissions from the previous year, and Length of stay. Further, the HOSPITAL score does not include interventions such as those listed in the BOOST tool to prevent potential readmissions.

BOOST Tool

In 2008, the Society of Hospital Medicine created the BOOST tool (Society of Hospital Medicine, 2015). Since its inception, more than 180 hospitals have participated in BOOST tool implementation (Williams et al., 2014). The BOOST tool with permission from the Society of Hospital Medicine is in Figure 2. The permission letter to reprint is in Appendix A. The BOOST tool identifies risk factors for readmission. Unlike the LACE+ and HOSPITAL score tools, the BOOST tool includes care coordination interventions that address medical and social determinants which may prevent unnecessary hospital readmissions.

Figure 2

BOOST 8P Screening Tool

project BOOST Better Outcomes by Optimizing Safe Transitions

The 8P Screening Tool
Identifying Your Patient's Risk for Adverse Events After Discharge

The 8Ps (Check all that apply.)	**Risk Specific Intervention**	**Signature of individual responsible for insuring intervention administered**
Problems with medications (polypharmacy – i.e. ≥10 routine meds – or high risk medication including: insulin, anticoagulants, oral hypoglycemic agents, dual antiplatelet therapy, digoxin, or narcotics) ☐	☐ Medication specific education using Teach Back provided to patient and caregiver ☐ Monitoring plan developed and communicated to patient and aftercare providers, where relevant (e.g. warfarin, digoxin and insulin) ☐ Specific strategies for managing adverse drug events reviewed with patient/caregiver ☐ Elimination of unnecessary medications ☐ Simplification of medication scheduling to improve adherence ☐ Follow-up phone call at 72 hours to assess adherence and complications	
Psychological (depression screen positive or history of depression diagnosis) ☐	☐ Assessment of need for psychiatric care if not in place ☐ Communication with primary care provider, highlighting this issue if new ☐ Involvement/awareness of support network insured	
Principal diagnosis (cancer, stroke, DM, COPD, heart failure) ☐	☐ Review of national discharge guidelines, where available ☐ Disease specific education using Teach Back with patient/caregiver ☐ Action plan reviewed with patient/caregivers regarding what to do and who to contact in the event of worsening or new symptoms ☐ Discuss goals of care and chronic illness model discussed with patient/caregiver	
Physical limitations (deconditioning, frailty, malnutrition or other physical limitations that impair their ability to participate in their care) ☐	☐ Engage family/caregivers to ensure ability to assist with post-discharge care assistance ☐ Assessment of home services to address limitations and care needs ☐ Follow-up phone call at 72 hours to assess ability to adhere to the care plan with services and support in place.	
Poor health literacy (inability to do Teach Back) ☐	☐ Committed caregiver involved in planning/administration of all discharge planning and general and risk specific interventions ☐ Post-hospital care plan education using Teach Back provided to patient and caregiver ☐ Link to community resources for additional patient/caregiver support ☐ Follow-up phone call at 72 hours to assess adherence and complications	
Patient support (social isolation, absence of support to assist with care, as well as insufficient or absent connection with primary care) ☐	☐ Follow-up phone call at 72 hours to assess condition, adherence and complications ☐ Follow-up appointment with appropriate medical provider within 7 days after hospitalization ☐ Involvement of home care providers of services with clear communications of discharge plan to those providers ☐ Engage a transition coach	
Prior hospitalization (non-elective; in last 6 months) ☐	☐ Review reasons for re-hospitalization in context of prior hospitalization ☐ Follow-up phone call at 72 hours to assess condition, adherence and complications ☐ Follow-up appointment with medical provider within 7 days of hospital discharge ☐ Engage a transition coach	
Palliative care (Would you be surprised if this patient died in the next year? Does this patient have an advanced or progressive serious illness? "No" to 1st or "Yes" to 2nd = positive screen) ☐	☐ Assess need for palliative care services ☐ Identify goals of care and therapeutic options ☐ Communicate prognosis with patient/family/caregiver ☐ Assess and address concerning symptoms ☐ Identify services or benefits available to patients based on advanced disease status ☐ Discuss with patient/caregiver role of palliative care services and the benefits and services available to the patient	

Note. Reprinted with permission from Society of Hospital Medicine

The reliability and validity of the BOOST tool have been evaluated in prior studies. Hansen et al. (2013) identified inconsistencies in hospital site reporting of patient discharges, which threatened reliability of the BOOST tool. Additionally, some of the hospital sites were unable to produce outcome statistics and lack of quality improvement resources posed a threat to validity. Similarly, Williams et al. (2014) found that lack of physician and leadership support including limited resources, led to inconsistencies in practice of BOOST documentation, threatening validity and reliability. Further, Sieck et al. (2019) showed poor predictive validity of the BOOST tool in the domains of palliative care and principal diagnosis in predicting readmissions. Accordingly, Robertson (2017) did not find a predictive significance in congestive heart failure and COPD readmissions when using a modified BOOST version, which threatened validity and reliability of the modified BOOST tool. On the other hand, Hansen et al. (2013) calculated a 2% readmission reduction when using the BOOST tool, which indicated that the BOOST tool was reliable and valid in decreasing readmissions.

Discharge planning from hospital to home involve multiple factors. The quality of care coordination involving transition from hospital to home is essential in preventing poor health outcomes that lead to unnecessary hospital readmissions. Prior to hospital discharge, the BOOST tool can be useful as a discharge checklist for discussion by the multidisciplinary healthcare team and the patient. Additionally, the BOOST tool includes medical and psychosocial components that are risk factors for readmissions and higher length of stays if not addressed prior to hospital discharge. BOOST tool implementation may standardize care coordination and discharge planning practices for the sepsis population.

Healthcare Facilities and BOOST Tool Application

Healthcare facilities within the United States and the United Kingdom have adopted the BOOST tool to reduce readmission rates and decrease hospital length of stays. Hansen et al. (2013) found a 2% reduction rate in readmissions and the total length of hospital stay decreased by 0.5 days at 11 large academic healthcare centers across the United States. Similarly, Lee et al. (2016) reported that the BOOST tool predicted 90% of acute medical readmissions with the use of two or more risk factors in a study conducted in the United Kingdom. Likewise, Sieck et al. (2019) found that the variables including health literacy (p = .030), depression (p = .003), problem medications (p = .001), physical limitations ($p \leq .001$), and prior hospitalizations ($p \leq .001$) were significant indicators for 30-day readmissions. Conversely, Williams et al. (2014) cited several barriers in BOOST use that included administrative support, timing, providing proper resources, staff engagement, and interdisciplinary team understanding of the discharge process. The BOOST tool provides a checklist of best practices for the interdisciplinary healthcare team in discharge planning and follow-up care. Lack of team engagement and variances in practice on BOOST tool implementation prior to hospital discharge may lead to unnecessary readmissions.

Healthcare facilities in the United States have modified the BOOST tool. The partner site for this quantitative study slightly modified the BOOST tool by adding the sepsis diagnosis under the principal diagnosis domain. Similarly, a Midwest facility in the

United States modified the BOOST tool by adding the primary care provider interaction category, and Robertson (2017) found that for COPD patients in the Midwest facility, problems with medications was a leading indicator for readmissions. For congestive heart failure patients, prior hospitalization was a leading indicator for readmissions. BOOST tool implementation in the hospital setting may be a viable option in predicting and preventing unnecessary hospital readmissions for the sepsis population.

BOOST Variables (The 8Ps)

Problems with Medications

A common reason for patients returning to the hospital is the lack of patient understanding about medication usage. Problems with medications within the BOOST tool include medications that are at high risk such as insulin, anticoagulants, oral hypoglycemics, antiplatelet therapy, digoxin, or narcotics (Society of Hospital Medicine, 2015). Problems with medications also include polypharmacy (Society of Hospital Medicine, 2015). Within the BOOST tool, polypharmacy is defined as the usage of 10 or more medications (Society of Hospital Medicine, 2015).

The relationship between polypharmacy and hospital readmissions was investigated by Sehgal et al. (2013), Picker et al. (2015), Lee et al. (2016), and Sieck et al. (2019). Since the rise in legislative and insurance payor concerns about hospital readmissions, researchers such as these have found that polypharmacy increases hospital readmission risk. Sehgal et al. found that readmissions that occurred 1 day after hospital discharge were polypharmacy-related ($p < .05$). Similarly, Picker et al. revealed a statistically significant relationship between polypharmacy and hospital readmissions (*p*

< .001). Additionally, Lee et al. indicated that polypharmacy related to 88% of readmissions in the United Kingdom. Further, Sieck et al. measured the odds of elderly patients' readmissions were 1.57 times higher than those prescribed less than 10 medications.

Based on evidence from prior studies by Sehgal et al. (2013), Picker et al. (2015), Lee et al. (2016), and Sieck et al. (2019), there is a link between polypharmacy and hospital readmissions, which supports the BOOST tool concept of polypharmacy. Lack of patient understanding on medication regime such as multiple antibiotic use for patients with sepsis, is a common reason for readmissions. Inappropriate medication usage, either over-medicating or under-medicating, or non-compliance with prescribed medications, may lead to adverse events, causing a hospital readmission. Interventions listed within the BOOST tool to address polypharmacy and high-risk medications include the teach back method, medication scheduling, and a follow-up call within 72 hours post discharge to evaluate compliance and complications (Society of Hospital Medicine, 2015).

Psychological Factors

The relationship between mental health disorders and hospital readmissions has been investigated by previous researchers. Readmission for mental health disorders has become a national concern in the United States due to the limited availability of inpatient psychiatric facilities. There is a high readmission risk related to psychological factors (Aubert et al., 2016; Cancino et al., 2014; Health Catalyst, 2017; Navathe et al., 2018; Sieck et al., 2019). The 30-day readmission rate for mood disorders is 15% (Health Catalyst, 2017). Approximately 22.4% of patients diagnosed with schizophrenia are readmitted (Health Catalyst, 2017). Cancino et al. (2014) found that patients with depressive symptoms had a higher possibility of hospital readmission 30 days post-discharge compared to patients without depressive symptoms. Similarly, Navathe et al. (2018) cited that the readmission rate for patients diagnosed with depression was 20.6% and 20.2% for drug abuse conditions. Additionally, Carter et al. (2020) reported that substance abuse disorder (p = .03) had an increased probability of preventable readmissions. Likewise, Sieck et al. (2019) posited that the odds of readmission for patients with depression was 1.61 times higher than those without a psychological condition. Notably, Arshad et al. (2020) showed that sepsis survivors are at high risk for developing mental illness, cognitive impairment, sleep deprivation, delirium, and depression. Further, Iwashyna et al. (2010) found a 10.6% increase in cognitive impairment for severe sepsis survivors.

Based on evidence from prior studies by Arshad et al. (2020), Cancino et al. (2014), Carter et al. (2020), Iwashyna et al. (2010), Navathe et al. (2018), and Sieck et al. (2019), psychological factors have a positive association with hospital readmissions. Psychological factors such as long-term cognitive impairments for sepsis survivors have a profound effect on quality of life and independence, which may impose increased burdens on families and caregivers, leading to frequent readmissions. Interventions listed within the BOOST tool to address psychological factors include depression screening, evaluation of the need for psychiatric care, and establishment of a support network (Society of Hospital Medicine, 2015).

Principal Diagnosis

Principal diagnosis such as sepsis, is a predictor for readmissions. Primary index diagnoses may be preventable readmissions, often related to underlying comorbidities (Donze et al., 2013). Donze et al. found that out of 22.3% of readmissions from an academic medical center, 8% were preventable readmissions, including respiratory infections, septicemia, and urinary tract infections. Further, Kim et al. (2019) discovered that out of 2,062 septic shock survivors, 690 had readmissions 90 days post discharge. A review of principal diagnosis is essential in the identification of potential readmissions. DeMerle et al. (2017) showed that the sepsis diagnosis is related to readmissions for recurrent sepsis. Notably, Donze et al. emphasized that it is essential to focus on both the primary diagnosis and the underlying comorbidities in care coordination and discharge planning. It is necessary for patients and caregivers to understand sepsis as a principal diagnosis, including strategies for symptom management in disease progression to prevent readmissions. Interventions within the BOOST tool to address principal diagnosis as a predictor for readmissions include patient education on their diagnosis, use of the teach back method, and discussions including national discharge guidelines specific to the diagnosis (Society of Hospital Medicine, 2015).

Physical Limitations

Lack of independent functioning with activities of daily living is a common factor in patients returning to the hospital. Another reason for unnecessary hospital readmission may be a lack of discussion on patient functional status (Greysen et al., 2014). There is an association between physical limitations and hospital readmissions (Falvey et al., 2016;

Sieck et al., 2019; Smith et al., 2010; Tonkikh et al., 2016). Smith et al. (2010) found that patients who were non-compliant with physical therapist recommendations and follow-up instructions had a readmission rate 2.9 times more than those who were compliant with physical therapist recommendations. Similarly, Falvey et al. (2016) showed that physical therapy involvement is crucial during and within 30 days post hospital discharge to optimize a patient's functional capacity and to prevent unnecessary readmissions. Additionally, Tonkikh et al. (2016) cited that readmissions were related to a decline in activities of daily living. Further, Prescott and Angus (2018) emphasized that sepsis survivors lack self-care education and support that is necessary after physical impairments occur related to a sepsis hospitalization. Recently, Aranha et al. (2020) found that frailty scores had an association with readmissions ($p = .001$). Based on evidence from these prior studies, physical limitations including frailty and deconditioning linked to hospital readmissions, which supports the concept of physical limitations in the BOOST tool.

Overlooking physical limitations at home, lack of caregiver support, and an evaluation of home safety during a sepsis hospitalization is essential to address prior to discharge to prevent unnecessary readmissions. A network of support systems to assist patients after a hospitalization is vital in preventing functional decline. Interventions within the BOOST tool to address physical limitations include family and caregiver engagement in post-discharge care, arrangement of home healthcare services including nursing visits and physical therapist visits, and a follow-up call 72 hours post-discharge to evaluate compliance with the support services provided (Society of Hospital Medicine, 2015).

Poor Health Literacy

Lack of patient understanding in their medical regime is another concern with hospital readmissions. Mitchell et al. (2012) emphasized that poor health literacy related to lack of compliance with medical regime, lack of understanding of discharge instructions including disease management and medication side effects, poor self-care, increased hospitalizations, mortality, and poor patient health outcomes. Likewise, Sieck et al. (2019) indicated that poor health literacy is the inability of the patient or caregiver to understand or reiterate medical and self-care regime. Similarly, Wallace et al. (2016) specified that low health literacy, often overlooked as one of the variables leading to frequent readmissions, is a barrier to self-management, which poses potential risk for poor health outcomes. Additionally, Wallace et al. found that there were differences in knowledge subscale scores between the literacy levels indicating that low health literacy is indicative of readmissions. Further, Choudhry et al. (2019) reported a decrease from 21.9% to 9% in patients calling the nurses station after a hospital discharge, and the monthly hospital readmission rate decreased by 50% when patients received simplified discharge instructions. Based on evidence from these prior studies, poor health literacy has an association with hospital readmissions, which supports the concept of poor health literacy in the BOOST tool. Therefore, it is crucial for the interdisciplinary healthcare team to evaluate the patient’s health literacy level and provide discharge instructions that the patient can understand.

Overlooking poor health literacy may occur during a hospitalization for a patient with sepsis. It is essential, therefore, to address patient and caregiver understanding of a simplified discharge and follow-up care plan for patients with sepsis, which includes support services and community resource linkage. It is necessary to review health literacy prior to a hospital discharge to empower patients and caregivers in self-care regime. Interventions listed in the BOOST tool to address poor health literacy include education on the discharge and follow-up care plan for patients and caregivers using the teach back method, linkage to community support resources, and a 72-hour follow-up call to evaluate compliance and complications (Society of Hospital Medicine, 2015).

Patient Support

Lack of patient support post-hospital discharge is a common factor in patients returning to the hospital. Patients without support from family and friends is an overarching theme in readmissions, particularly for the elderly and vulnerable populations (Chan et al., 2019; Greysen et al., 2014; Navathe et al., 2018). Adisa et al. (2018) found that unmarried hemodialysis patients were 38% more likely to be readmitted. Those who were widowed had a 17% likelihood of being readmitted. Similarly, Navathe et al. (2018) calculated that patients with poor social support had a 20% higher readmission risk compared to patients with a stable support system. Additionally, Navathe et al. reported that patients with housing instability had a 24.5% higher readmission risk than those with housing stability. Likewise, Carter et al. (2020) found that patients with a history of homelessness had an increased probability of preventable readmissions. Further, Chan et al. (2019) discovered a 50% lower possibility of readmissions among patients with high social support compared to those with low social support. Based on evidence from these prior studies, there is a link between inadequate support systems and readmission risk, which highlights the concepts of patient support in the BOOST tool.

Legislation should implement an enhanced social policy for preventable readmissions related to lack of social support (Carter et al., 2020). In addition to an assessment of the support systems in the patient's home, it is also necessary to evaluate the social support systems accessible to the patient in the community. It is vital to strengthen social policy for the sepsis population to address the following social determinants of health: (a) access to medical care, (b) health insurance coverage, (c) healthy food, (d) transportation, (e) safe and affordable housing, and (f) socioeconomic needs. Social determinants of health affect quality of life, which pose a potential readmission risk, resulting in additional burden of healthcare cost. Frequent readmissions have an association with social admits as patients return to the emergency department seeking assistance for access related to the social determinants of health. Lack of access to healthcare, healthy food, and safe housing results in poor health outcomes, causing a readmission. BOOST tool interventions to address patient support includes provision of home health resources, arrangement of follow-up care within 7 days after discharge, and a 72-hour follow-up call to evaluate compliance and complications (Society of Hospital Medicine, 2015).

Prior Hospitalization

Previous researchers found an association between prior hospitalizations and readmissions. Prior hospitalizations link with readmissions particularly after an index (initial) admission (Kim et al., 2019; Lin et al., 2019; Shankar-Hari et al., 2020; Sieck et al., 2019). Lin et al. (2019) found that patients with greater than five hospitalizations had a 31.2% probability of 30-day readmissions after an index (initial) hospitalization. Additionally, Kim et al. (2019) identified that 13.3% of septic shock patients had readmissions from a prior hospitalization related to septic shock. Further, Singh et al. (2019) found that prior hospitalizations within 1 year was statistically significant to readmissions ($p < .01$). Recently, Shankar-Hari et al. (2020) confirmed that sepsis readmissions are common within 30 days post-discharge when the index (initial) admission related to sepsis. Notably, Sieck et al. (2019) reported that prior hospitalizations related to readmissions when the BOOST tool was used as a risk stratification tool in predicting 30-day readmissions. Based on evidence from these prior studies, prior hospitalizations are related to readmissions, which supports the concept of prior hospitalization in the BOOST tool. Patients who lack understanding of the rationale for their prior hospitalizations and disease management such as sepsis, may be at risk for readmissions. It is essential for the multidisciplinary team to review the course of prior hospitalizations to evaluate for conditions that may continue to result in frequent readmissions. Interventions within the BOOST tool to address prior hospitalization include a review of the disease process and readmission related to prior hospitalizations, follow-up care appointments within 7 days of discharge, and a follow-up call within 72 hours after discharge to assess for compliance and complications (Society of Hospital Medicine, 2015).

Palliative Care

Palliative care services may be necessary to prevent readmissions in long-term care patients. Palliative care involves goals of care, advanced care planning, and emotional and physical comfort in end-of-life care (Ranganathan et al., 2013). Home-based palliative care in the United States has become a common discharge plan for patients who are severely ill (Ranganathan et al., 2013). Ranganathan et al. found that 9.1% of patients who had palliative care services at home were likely to be readmitted 30 days after discharge, which was a lower probability compared to patients without palliative home care services. Similarly, DiMartino et al. (2018) indicated that patients with an inpatient palliative care consult with a hospice discharge were less likely to be readmitted within 30 days post-discharge. Recently, Aranha et al. (2020) determined that palliative performance scores strongly predicted the possibility of hospital readmissions (p = .001). Based on evidence from these prior studies, patients at end of life linked with palliative care services, have a lower probability of readmissions, which supports the concept of palliative care in the BOOST tool.

Palliative care is often overlooked as a choice for patients suffering from long-term conditions with minimal curative options. Palliative care may decrease frequent hospital readmissions and preserve quality of life for patients with sepsis at end of life. BOOST tool interventions to address palliative care include patient and family discussions on the prognosis, disease progression, treatment options, and palliative care services (Society of Hospital Medicine, 2015).

Control Variables

Age

Prior researchers investigated the relationship between age and readmissions and age and length of stay. Berry et al. (2018), Donnelly et al. (2015), Goodwin and Ford (2018), and Stenholt et al. (2021) evaluated the relationship between age and readmissions. Berry et al. identified an association between multiple chronic conditions with readmissions amongst patients aged 16 years and older, and the most common index diagnosis was mental health for children, young adults, and middle-aged adults ($\geq 75^{th}$ percentile). Additionally, Donnelly et al. found that patients 18 years and older with severe sepsis had an unplanned 30-day readmission rate at 64.2%. Notably, Stenhold et al. found that elderly patients (median age 74.9 years) with a baseline history of sepsis within the past year were likely to be readmitted within 90 days post hospital discharge. In contrast, Goodwin and Ford discovered that the younger population and the population over 80 years had a lower probability of readmissions related to sepsis. Recently, Guo et al. (2021) found that there was no statistically significant relationship between age (p = .64) and length of stay in COVID-19 patients. Based on these prior studies, there are controversial findings on age and the relationship to sepsis readmissions.

Gender

Prior studies examined the relationship between sepsis readmissions and gender. Goodwin and Ford (2018) cited that 48.1% of females who were severe sepsis survivors had readmissions 30 days after a hospital discharge. On the other hand, Donnelly et al. (2015) found that males with severe sepsis had a higher percentage rate (50.6%) for readmissions compared to females with a percentage rate of 49.4% for readmissions. In contrast, Goodwin and Ford found a weak relationship between gender and readmissions. Based on findings from these previous researchers, there is a controversy on the relationship between gender and sepsis readmissions.

Health Insurance Coverage

Prior researchers have identified that there is a relationship between health insurance coverage, readmissions, and length of stay. Goodwin and Ford (2018) found that for severe sepsis survivors, the readmission rate for patients with Medicare was 65.5%, for Medicaid patients, the readmission rate was 14.1%, and for patients with commercial insurance, the readmission rate was 11.1%. Similarly, Donnelly et al. (2015) cited that Medicare patients with severe sepsis had a readmission rate of 66.5%, Medicaid patients had a readmission rate of 16.6%, commercial pay patients had a readmission rate of 12.2%, and self-pay patients had a readmission rate of 3%. Additionally, Berry et al. (2018) reported that the type of insurance payor significantly affected readmissions ($p < .001$). For patients with private insurance, the readmission rate was 7%. The readmission rates were 10.1% and 16.4% for patients with and without Medicare, respectively. Based on findings from these prior studies, there is a significant relationship between health insurance coverage and sepsis readmissions. Medicare recipients had a higher readmission rate compared to Medicaid and commercial payor recipients. Further, Englum et al. (2016) found that uninsured patients had a shorter length of hospital stay by

0.3 days compared to privately insured patients. Similarly, Mainous et al. (2011) discovered that uninsured patients had a decreased length of stay (2.77 days) compared to patients who were privately insured (2.89 days) or publicly insured (3.19 days).

Synthesis of Studies Related to RQs

RQs

Three RQs guided this quantitative study. The first RQ centered on the relationship between BOOST tool implementation and hospital readmission for patients with sepsis. To answer the second RQ, I analyzed the relationship between BOOST tool implementation and average length of stay in patients with sepsis. The third RQ posed the relationship between BOOST tool implementation and patient satisfaction scores related to discharge instructions for patients with sepsis.

Care Coordination and Sepsis Readmissions

Effective care coordination strategies are essential in preventing unnecessary readmissions in patients after a sepsis-related hospitalization. Prior studies by Kowalkowski et al. (2019), Meyer et al. (2018), and Taylor et al. (2019) indicated that appropriate sepsis care coordination reduced readmissions and mortality rates. Best practices in post-sepsis care coordination improved health outcomes for high-risk patients (Kowalkowski et al., 2019). Standardization of care coordination by avoiding variations in practice for post-sepsis care elements decreases morbidity and mortality and increases positive health outcomes for sepsis survivors (Taylor et al., 2019). Meyer et al. found that care coordination including continuity of care, from the inpatient setting to post-acute care, antibiotic regimen, sepsis specific impairment monitoring, and tracking of new or recurrent infections is essential in readmission reduction and mortality rates. Similarly, the findings by Taylor et al. (2020) indicated that the application of four best practice elements (medication management=62% of the sample, odds ratio 0.44; health deterioration monitoring=46% of the sample, odds ratio 0.42; functional impairment screening=65% of the sample, odds ratio 0.14, and palliative care consideration=58% of the sample, odds ratio 0.52) decreased readmissions and mortality rates within 90 days post hospitalization for the sepsis population. Care coordination strategies such as those listed in the BOOST tool could prevent unnecessary sepsis readmissions.

The elements in the BOOST tool allow for standardization of care coordination practices within the multidisciplinary healthcare team. Lee et al. (2016) found that the BOOST tool predicted 90% of readmissions in the United Kingdom. Similarly, Sieck et al. (2019) found that the risk factors in the BOOST tool including health literacy, depression, polypharmacy, physical limitations, and prior hospitalizations, were associated with 30-day readmissions in elderly patients. Based on evidence from prior studies by Kowalkowski et al. (2019), Lee et al. (2016), Meyer et al. (2018), Sieck et al. (2019), and Taylor et al. (2020), BOOST tool implementation may be a viable option in improvement of care coordination efforts to prevent unnecessary readmissions in sepsis patients. Low sepsis readmission rates could be indicative of effective care coordination strategies.

Care Coordination and Length of Stay in Patients with Sepsis

One factor that reflects the quality of care coordination provided is hospital length of stay. The definition of the length of stay is a single hospitalization which includes the number of days a patient stays in the hospital from admission date to discharge date (Baek et al., 2018). Longer length of stay increases patient risk for acquiring nosocomial infections that later lead to increased risk for readmissions (Singh et al., 2019). Decreased length of stay is a quality metric in care coordination, which reflects hospital management including risk reduction for infections and medication side effects (Baek et al., 2018). In the acute care setting, each diagnosis receives an average length of stay that determines the expected hospital stay for that diagnosis. A comparison occurs between the expected days of hospital stay to the actual number of days the patient stayed in the hospital. The actual number of days the patient stayed in the hospital may differ than the predicted average length of stay.

The findings of prior studies by Mayr et al. (2017), McCoy and Das (2017), and Singh et al. (2019) showed the relationship between sepsis and length of hospital stay. Mayr et al. found that readmitted sepsis patients had a higher length of stay (7.4 days) compared to patients with a diagnosis of pneumonia (6.7 days), congestive heart failure (6.4 days), COPD (6.0 days), and acute myocardial infarction (5.7 days). Additionally, McCoy and Das revealed that the implementation of a sepsis algorithm decreased sepsis length of stay by 9.55%. Comparably, Singh et al. cited that 52% of sepsis readmissions were related to infectious causes and that length of stay was not statistically significant to readmissions (p = .371). Based on evidence from these prior studies, sepsis readmissions had a higher length of stay compared to other conditions and length of stay decreased with care coordination implementations, such as the sepsis algorithm in the McCoy and Das study.

Care Coordination and Patient Satisfaction

Patient satisfaction is the patient experience before, during, and after hospitalization (Berkowitz, 2016). The CMS Quality Strategy created quality measures to engage patients and caregivers in care coordination and effective communication with clinical providers (Berkowitz, 2016). High patient satisfaction scores are related to effective discharge planning and lower readmission rates (Boulding et al., 2011).

Prior researchers found a link between patient satisfaction and the quality of care provided by the multidisciplinary team and the healthcare organization. Figueroa et al. (2018), Huang et al. (2016), and Wang et al. (2015) examined the relationship between care coordination and patient satisfaction. Wang et al. revealed that there was a positive relationship between care coordination, discharge planning, and patient satisfaction. The odds ratio for overall care coordination and patient satisfaction was 1.78. Similarly, Figueroa et al. reported that hospitals experienced high patient satisfaction scores when they provided discharge summaries, medication education, discharge coordinators, and follow-up phone calls 48 hours post discharge. In comparison to other countries, Huang et al. found that sepsis survivors from the United Kingdom were most satisfied with sepsis care coordination compared to other countries. In contrast, Quinn et al. (2017) identified patient concerns in care coordination on trusting relationships with the clinical provider, ease of medical record access by the provider, continuity of care with other providers across the healthcare continuum, and follow-up care including obtaining physician appointments, clinical tests and procedures, and medical regimens. Based on findings from these prior studies, patients expressed satisfaction with care coordination and discharge planning when they were provided education on self-care, medical regimen, and follow-up care. Patient satisfaction scores in the discharge domain could be indicative of the quality of discharge planning provided.

Surveys such as Press Ganey capture the patient experience and the quality of care provided. Domains in Press Ganey (Appendix F) use a rating scale based on a 1 to 5 Likert scale for quality of services related to the following: admission, room, meals, nurses, tests and treatments, visitors and family, physician, discharge information, personal issues, and overall assessment (Press Ganey, 2020). Rasudin et al. (2019) investigated the reliability and validity of the Press Ganey survey; the average variance was 0.50, which met validity standards. The reliability score was 0.966, which met reliability standards. The Press Ganey Survey measures patient satisfaction with discharge readiness.

Gaps in Prior Studies

Although the BOOST tool has been applied to other conditions in prior studies, there is limited data on the analysis of BOOST tool implementation and the relationship to readmissions, length of stay, and patient satisfaction for patients with sepsis. Prior studies by Hansen et al. (2013), Lee et al. (2016), Robertson (2017), and Sieck et al. (2019) investigated the BOOST tool variables, but did not consider readmissions, length of stay, and patient satisfaction in the sepsis population. Hansen et al. found a 2% readmission reduction and a decrease by 0.5 days in length of stay in 11 U.S. hospitals that implemented the BOOST tool and mentorship was a key element in sustained organizational efforts to propel the BOOST initiative. However, the Hansen et al. study did not consider the sepsis population. Incidentally, Robertson cited that patients with COPD had a greater readmission risk with polypharmacy and principal diagnosis as BOOST predictor variables. Patients with congestive heart failure had a greater readmission risk with prior hospitalization as the BOOST predictor variable. Similarly, Lee et al. related BOOST variables, polypharmacy, and prior hospitalizations, to readmissions. Likewise, Sieck et al. found that BOOST variables including polypharmacy, psychological factors, physical limitations, poor health literacy, and prior hospitalizations, were associated with readmissions. The BOOST tool in these prior studies was used as a predictor model to assess which variables would predict the greatest risk for readmissions, indicating that the BOOST tool may be a viable option in preventing unnecessary readmissions; however, the sepsis population was not considered in these prior studies.

Summary and Conclusions

Major themes in the literature include care coordination, sepsis readmissions, length of stay, and patient satisfaction. Additional themes include readmission reduction mandates, risk stratification tools such as the LACE+, HOSPITAL score, and the BOOST tool. The components of the BOOST tool kit, which includes the eight primary reasons for readmission were highlighted and discussed in this chapter.

Prior to the BOOST tool, the partner site for this quantitative study used the LACE+ score, a high score on which indicated readmission risk. The LACE+ score, however, does not include interventions such as those outlined in the BOOST tool that serve as a checklist to avoid unnecessary readmissions. The interventions listed within the BOOST tool allow for standardization of care to prevent variances in practice.

The framework for this quantitative study was based on the relational coordination theory. The concepts of relational coordination theory are based on shared goals, team communication, and standardization in practice, leading to performance metrics in quality and efficiency. Applying relational coordination to this quantitative study was appropriate because the BOOST tool is a structured format for standardization in practice, allowing for consistency in practice among members of the multidisciplinary team, which fosters frequent team communication, and goal sharing, to improve patient health outcomes.

The findings of this quantitative study could extend knowledge in the field through investigation of care coordination implementations and hospital outcomes including readmissions, length of stay, and patient satisfaction in patients with sepsis. Sepsis readmissions are costly and potentially lead to poor patient outcomes. Prior researchers evaluated the BOOST tool; however, the sepsis population was not included in these prior studies. Length of stay is a quality metric in care coordination. Prior researchers have investigated the relationship between sepsis and length of stay without using the BOOST tool. Long hospital stays increase the potential risk of contracting hospital-acquired conditions, which intensifies the mortality risk for the sepsis population. Patient satisfaction is associated with the quality of care provided by the healthcare organization. Prior researchers examined patient satisfaction in the sepsis population; however, satisfaction with BOOST tool implementation was not evaluated in these prior studies.

Chapter 3 includes a discussion of the research design and rationale, methodology, and threats to validity for this study. The current study is quantitative in nature, and the collected data was secondary. The data analysis plan included multiple logistic regression and multiple linear regression. Chapter 3 concludes with a detailed exposition of the methodology and related literature supporting the design of this quantitative study.

Chapter 3: Research Method

Sepsis is a severe infection that results in frequent readmissions, high length of hospital stays, and poor outcomes in comparison to patients with other conditions (Hajj et al., 2018; Mayr et al., 2017). Thus, sepsis morbidity and mortality are a global concern (Salomao et al., 2019). There is a gap in the literature on the relationship between BOOST tool implementation and hospital outcome quality measures in readmissions, length of stay, and patient satisfaction in the sepsis population. The purpose of this quantitative study was to investigate the relationship between BOOST tool implementation and hospital outcomes including readmissions, length of stay, and patient satisfaction for patients with sepsis.

In Chapter 3, I present and justify the methodology that guided this quantitative study. This includes variable operationalization of BOOST tool implementation, readmissions, and length of stay. I also discuss the data analysis plan, including the use of multiple logistic regression and multiple linear regression. Chapter 3 concludes with a consideration of the ethical integrity of this study.

Research Design and Rationale

In this quantitative study, I used multiple logistic regression and multiple linear regression to conduct secondary data analysis. I compared data from January 2017 to June 2019 before BOOST implementation to data from the years July 2019 to April 2021 after BOOST implementation. There were no time and resource constraints identified with this design choice.

A comparison of variables prior to and following BOOST implementation enabled me to assess whether BOOST implementation was associated with readmissions (RQ 1) and length of stay (RQ 2). The independent variable was BOOST tool implementation, and the dependent variables were readmissions and length of stay. The control variables were age, gender, health insurance coverage, and disease state (i.e., sepsis, severe sepsis, septic shock). Logistic regression analysis was appropriate for this study because it enabled me to calculate the odds probability of an outcome and define its relationship to the independent variables and control variables (Stoltzfus, 2011). To answer RQ 1, I employed multiple logistic regression to determine the odds of readmissions after BOOST tool implementation. Multiple logistic regression analysis was appropriate for this study because it examined the relationship of an independent variable and a continuous outcome (Stoltzfus, 2011). For RQ 2, multiple linear regression was used to examine the linear relationship between BOOST tool implementation and length of stay from the index (initial) admission. To address RQ 3, multiple linear regression was initially proposed to examine the linear relationship between BOOST tool implementation and patient satisfaction. However, during the data collection phase, the analytics and informatics team at the partner site were only able to provide aggregated data from the Press Ganey surveys. Therefore, due to lack of access at the respondent level, I conducted a simple descriptive analysis without significance testing for RQ 3.

Methodology

I collected de-identified data of hospitalized males and females 18 years and older with an index (initial) and readmission diagnosis of sepsis, severe sepsis, or septic shock.

The dataset included a mixed population of patients diagnosed with sepsis, severe sepsis, or septic shock. An examination of the BOOST tool implementation by the multidisciplinary healthcare team occurred in relation to hospital readmissions, length of stay, and patient satisfaction scores. The remainder of this section is organized by subsections related to the target population, sampling strategy, archival data, instrumentation, operationalization of constructs, and data analysis plan.

Population

The target population included hospitalized males and females 18 and older with an index (initial) and readmission diagnosis of sepsis, severe sepsis, or septic shock. Patients who had been readmitted 30 days after a sepsis hospitalization were included in the target population. The target population came from one short-term, 800-bed, acute care hospital. The partner site, located in the West Coast region of the United States, implemented the BOOST tool in July 2019.

Sampling and Sampling Procedures

Probability sampling was appropriate for this quantitative study to ensure that the chosen participants were representative of the population (Frankfort-Nachmias & Leon-Guerrero, 2018). The sample for RQ 1, RQ 2, and RQ 3, comprised of hospitalized patients with the index (initial) admission diagnosis of sepsis, severe sepsis, or septic shock from one academic healthcare system in the West Coast region of the United States. For RQ 1, 30-day readmissions were calculated from the index (initial) sepsis admission. For RQ 2, length of stay sample size was calculated based on the index (initial) sepsis admission. For RQ 3, patient satisfaction scores from Press Ganey were based on the index (initial) sepsis admission. Using the electronic source, I extracted de-identified archival data, with permission and assistance from the partner site's data extraction department and informatics and analytics department. This occurred after approval was received from Walden University's IRB and the partner site's IRB. The period of the data covered was from January 2017 to June 2019 (i.e., prior to BOOST implementation) and then from July 2019 to April 2021 (i.e., following BOOST implementation). July 2019 was chosen as a start date because this was the date of BOOST implementation at the partner site. Analysis of sepsis readmission and length of stay data prior to and following the implementation of the BOOST tool occurred.

Sampling Frame

I obtained the sample while considering several inclusion and exclusion criteria. Inclusion criteria comprised of hospitalized patients aged 18 years and older, males and females, admitted and readmitted with sepsis, severe sepsis, or septic shock diagnosis, admitted and readmitted within the health system of the partner site, and implementation of the BOOST tool during the hospitalization. Documentation of the implementation of the BOOST tool was in the patients' medical records. Exclusion criteria comprised of patients without a sepsis diagnosis, patients not within the specified age range, and patients not admitted or readmitted within the health system of the partner site.

Power Analysis

G* Power software is used to obtain the power analysis (Mayr et al., 2007). I used G* Power analysis software to calculate the sample size and the effect size for RQ 1, RQ 2, and RQ 3. An alpha level or *p* value of .05 was employed to identify the probability of error. A *p* value of .05 is the acceptance value of most researchers (Frankfort-Nachmias & Leon-Guerrero, 2018). The effect size establishes the relationship strength between two variables, and a greater effect size, indicates a stronger relationship between the variables (Frankfort-Nachmias & Leon-Guerrero, 2018). Conversely, a smaller effect size, reveals a weaker relationship between the variables.

The basis for the sample size in G* Power analysis for RQ 1 (BOOST implementation and readmissions) was on multiple logistic regression. The input parameters entered were as follows: tails = two, odds ratio = .25, effect size = .15, alpha level = .05, actual power = .95 in a binomial distribution. I chose a priori power analysis to determine adequate power prior to the study. The output parameters entered were as follows: critical z = -1.9599640, actual power = .9502507. The total minimal sample size calculated for RQ 1 was 131 sepsis admissions (Appendix C). For RQ 1, I estimated 10 sepsis readmissions per month before BOOST implementation (January 2017–June 2019), for a total of 290 sepsis readmissions (10 readmissions/month x 29 months), which was greater than the calculated minimal sample size of 131 sepsis admissions. After BOOST implementation (July 2019–April 2021), I estimated eight sepsis readmissions per month, for a total of 168 (eight readmissions/month x 21 months), which was greater than the calculated minimal sample size of 131 sepsis admissions. The actual sample size for RQ 1 was 1,394 sepsis admissions between the years 2017 to 2021, which was greater than the calculated minimal sample size of 131 sepsis admissions.

The basis for the sample size in G* Power analysis for RQ 2 (BOOST implementation and length of stay) was on multiple linear regression. The input parameters entered were as follows: tails = two, effect size = .15, alpha level = .05, actual power = .95, number of predictors = 5. There was one independent variable (BOOST tool implementation) and four control variables (age, gender, health insurance coverage, and disease state) and therefore five was the number entered under predictors. I used a priori analysis to determine adequate power prior to the research study. The output parameters entered were as follows: non-centrality parameter = 3.6537652, critical t = 1.9889598, df = 83, actual power = .9506518. The total minimal sample size calculated for RQ 2 was 89 sepsis participants (Appendix D). For RQ 2, I estimated 10 sepsis participants per month before BOOST implementation (January 2017–June 2019), for a total of 290 sepsis participants (10 sepsis participants/month x 29 months), which was greater than the calculated minimal sample size of 131 sepsis patients. After BOOST implementation (July 2019–April 2021), I estimated eight sepsis participants per month, for a total of 168 (eight sepsis participants/month x 21 months), which was greater than the calculated minimal sample size of 131 sepsis patients. The actual sample size for RQ 2 was 1,394 sepsis participants between the years 2017 to 2021, which was greater than the calculated minimal sample size of 131 sepsis participants.

The basis of the sample size in G* Power analysis for RQ 3 (BOOST implementation and patient satisfaction) was initially based on multiple linear regression. The input parameters entered were as follows: tails = two, effect size = .15, alpha level = .05, actual power = .95, number of predictors = 5. There was one independent variable (BOOST tool implementation) and four control variables (age, gender, health insurance coverage, and disease state) and therefore five was the number entered under predictors. I chose a priori analysis to determine adequate power prior to the research study. The output parameters entered were as follows: non-centrality parameter = 3.6537652, critical t = 1.9889598, df = 83, actual power = .9506518. The total minimal sample size calculated for RQ 3 was 89 sepsis respondents (Appendix E). For RQ 3, I estimated 10 sepsis patients responded to the Press Ganey survey per month before BOOST implementation (January 2017–June 2019), for a total of 290 sepsis respondents (10 estimated returned sepsis surveys/month x 29 months), which was greater than the calculated minimal sample size of 89 sepsis respondents. After BOOST implementation (July 2019–April 2021), I estimated eight sepsis patients responded to the Press Ganey survey per month for a total of 168 sepsis respondents (eight estimated returned sepsis surveys/month x 21 months), which was greater than the calculated minimal sample size of 89 sepsis respondents. The actual sample size for RQ 3 was 689 sepsis respondents between the years 2017 to 2021, which was greater than the calculated minimal sample size of 89 sepsis respondents.

Press Ganey Questions and Conversion Ratings to Scores

I obtained the discharge domain questions and conversion ratings from the partner site's Press Ganey liaison. The discharge domain questions from Press Ganey are as follows:

1. Extent to which you felt ready to be discharged
2. Speed of discharge process after you were told you could go home
3. Instructions given about how to care for yourself at home

4. Explanations regarding taking medicine after discharge (including potential side-effects)
5. How well the case manager assisted you with discharge planning

Press Ganey uses a Likert scale for each survey question with the following ratings: *Very Poor* = 1, *Poor* = 2, *Fair* = 3, *Good* = 4, *Very Good* = 5. Press Ganey then converts the ratings to a mean score on a scale of 0-100 for each answer: *Very Poor* = 0, *Poor* = 25, *Fair* = 50, *Good* = 75, *Very Good* = 100. The formula (x-1)*25 is used to convert the ratings to scores, where x = the value in the 0-5 rating scale. The conversion ratings to scores are as follows:

Rating=	Very Poor	Poor	Fair	Good	Very Good
	1	2	3	4	5
	↓	↓	↓	↓	↓
Score=	0	25	50	75	100

A mean score is the arithmetic average that represents the respondents' answers to the survey question(s).

Archival Data

Extraction of the archival data was performed by the informatics and analytics team from the electronic source of an academic healthcare system in the West Coast region in the United States. The archival data consisted of patients' age, gender, health insurance coverage, specific sepsis diagnosis, admission and readmission dates, length of hospital stay, and Press Ganey aggregated patient satisfaction scores. Collection of the archival data occurred after I received IRB approval from Walden University and IRB approval from the partner site. The signed data use agreement with the partner site was not needed as indicated by the IRB at the partner site and Walden University.

Variable Operationalization

The selected variables, type of scales used, and concept measurement were illustrated in Table 1. The independent variable was BOOST tool implementation. The dependent variables were readmissions and length of stay. The control variables were age, gender, health insurance coverage, and disease state (sepsis, severe sepsis, septic shock). In this section, I discussed the operationalization and measurement of each variable.

Table 1

Variable Operationalization

Independent variable	Scale	Measurement
BOOST tool implementation	Nominal scale 0=Before BOOST 1=After BOOST	0=Before BOOST tool implementation (admissions between January 2017-June 2019) 1=After BOOST tool implementation (admissions between July 2019-April 2021)
Dependent variables	Scale	Measurement
Readmissions	Nominal scale 0=No 1=Yes	Measurement of 30-day readmissions
Length of stay	Interval scale	Continuous measurement of inpatient days from database
Control variables	Scale	Measurement
Sex	Nominal scale 0=Female 1=Male	Participant gender
Age	Ordinal scale 1=18-40 years 2=41-64 years 3=65-74 years 4=75 years and older	Categorical variable
Health insurance	Nominal scale 1=Private insurance/other 2=Medicaid/self-pay 3=Medicare	Health insurance coverage Categorical variable
Disease state		
Categorical diagnosis	Scale	Measurement
Sepsis	Ordinal scale 1=Sepsis diagnosis	Participant with sepsis diagnosis as an inclusion criteria. Categorical variable.
Severe sepsis	Ordinal scale 2=Severe sepsis diagnosis	Participant with severe sepsis diagnosis as an inclusion criteria. Categorical variable
Septic shock	Ordinal scale 3=Septic shock diagnosis	Participant with septic shock diagnosis as an inclusion criteria. Categorical variable

The independent variable was BOOST tool implementation, which was a binary variable (yes/no) on a nominal scale. A code of 0 indicated before BOOST tool implementation (years January 2017–June 2019). A code of 1 indicated after BOOST tool implementation (years July 2019–April 2021).

Readmissions was a dependent variable. For this quantitative study, the 30-day readmission from the prior sepsis hospitalization was measured with a nominal scale. A code of 1 indicated a readmission. A code of 0 indicated no readmissions. Events related to 30-day sepsis readmissions were captured by selecting 30-day readmissions after the prior hospital discharge date. If the patient expired or left the hospital against medical advice, all the 30-day readmission events were still captured prior to the patient expiring or leaving against medical advice.

Length of stay was a dependent variable. Length of stay was a continuous measurement of inpatient days on an interval scale. For this quantitative study, length of stay was the number of hospital days the patient was hospitalized due to a sepsis, severe sepsis, or septic shock diagnosis from the index (initial) admission.

The control variables were age, gender, health insurance coverage, and disease state. For this study, gender had an assigned code of 0 for females and 1 for males on a nominal scale. Age was a categorical variable on an ordinal scale. A numeric code was assigned for 1 = ages 18-40 years, 2 = ages 41-64 years, 3 = ages 65-74 years, 4 = 75 years and older. The age categories were based on the population distribution. From the descriptive statistics and frequencies, the mean age was 63.9 years. Health insurance coverage was a categorical variable on a nominal scale. Health insurance coverage was assigned a code based on the type of insurance coverage. A code of 1 indicated private insurance coverage or other. A code of 2 indicated Medicaid coverage/self-pay. A code of 3 indicated Medicare coverage.

The partner site modified the BOOST tool to include sepsis under the principal diagnosis section. The three categories of disease state variables were sepsis, severe sepsis, and septic shock. As an indicator of severity, sepsis is an ordinal variable and a code of 1 was assigned on an ordinal scale. For this quantitative study, sepsis was a categorical variable. For the severe sepsis diagnosis, a code of 2 indicated a severe sepsis diagnosis on an ordinal scale. As an indicator of severity, severe sepsis was an ordinal variable. For this quantitative study, severe sepsis was a categorical variable.

For the septic shock diagnosis, a code of 3 indicated a septic shock diagnosis, on an ordinal scale. As an indicator of severity, septic shock can be an ordinal variable. For this quantitative study, septic shock was a categorical variable. Operationalization of the diagnoses of sepsis, severe sepsis, and septic shock came from the hospital billing records indicating the 10th edition of the international classification of disease codes (see Table 2).

Table 2

Diagnosis Codes

Diagnosis	ICD 10-CM Codes
Sepsis	A.41.9,A41.89,A41.50,A41.52,A41.8,A41.59
Severe sepsis	R65.2,R65.21
Septic shock	T81.10XD,T81.10XS,T81.12XA,T81.12XD,T81.12XS

Data Analysis Plan

The Statistical Package for Social Sciences (SPSS), version 27 (IBM) for Windows 10, was the statistical software of choice to analyze and store the data for this study. This quantitative study included data cleaning and screening for computer errors in data entry and retrieval. Along with the analytics and informatics team at the partner site, I evaluated for any computer errors. The cleaning procedure included an assessment of any missing values in SPSS. There were no missing values for the dataset in the years 2017 to 2021. SPSS was used to clean the data. The informatics and analytics team at the partner site was consulted to review any data entry and retrieval errors as part of the cleaning procedure.

Multiple regression was utilized to assess how multiple independent variables affect one dependent variable (Frankfort-Nachmias & Leon-Guerrero, 2018). Multiple regression investigates the predictive relationship between the predictor variables and the outcome variables (Creswell & Creswell, 2018). The statistical models that were utilized for this quantitative study were multiple logistic regression and multiple linear regression to test the hypotheses for the RQs:

- RQ 1: What is the relationship between BOOST tool implementation and the likelihood of hospital readmissions for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state?
- $H_0$1: There is no statistically significant relationship between BOOST tool implementation and the likelihood of hospital readmissions for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state.

- H_a1: There is a statistically significant relationship between BOOST tool implementation and the likelihood of hospital readmissions for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state.
- RQ 2: What is the relationship between BOOST tool implementation and average length of stay for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state?
- H_02: There is no statistically significant relationship between BOOST tool implementation and average length of stay for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state.
- H_a2: There is a statistically significant relationship between BOOST tool implementation and average length of stay for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state.
- RQ 3: What is the relationship between BOOST tool implementation and patient satisfaction scores for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state?
- H_03: There is no statistically significant relationship between BOOST tool implementation and patient satisfaction scores for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state.
- H_a3: There is a statistically significant relationship between BOOST tool implementation and patient satisfaction scores for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state.

Multiple logistic regression was employed to test the hypotheses associated with RQ 1. Multiple linear regression was employed to test the hypotheses for RQ 2. Due to lack of access at the respondent-level, the hypotheses in RQ 3 were not tested. A simple descriptive analysis without significance testing was used instead. The analyses determined the relationship between BOOST tool implementation, and the dependent variables of, readmissions and length of stay in patients with sepsis.

An example of a multiple regression equation is Y=α + $\beta_1 X_1$ + $\beta_2 X_2$ where Y= dependent variable, α=unstandardized coefficient of dependent variable when the independent variables are equal to zero, β_1 = independent variable, β_2=independent variable, and X_1=independent variable score (Frankfort-Nachmias & Leon-Guerrero, 2018). For this quantitative study, the multiple linear regression equation for the dependent variable of length of stay, can be written as Y=α + $\beta_1 X_1$ where Y=length of stay, α=unstandardized coefficient of length of stay when the independent variables are equal to zero, β_1=BOOST tool implementation, and X_1=BOOST tool implementation score. The multiple linear regression equation for the dependent variable of patient satisfaction, can be written as Y=α + $\beta_1 X_1$ where Y=patient satisfaction, α=unstandardized coefficient of patient satisfaction when the independent variables are equal to zero, β_1=BOOST tool implementation, and X_1=BOOST tool implementation score.

The coefficients table tests the relationship between the independent and dependent variables, which indicates whether the regression model is a good fit (Frankfort-Nachmias & Leon-Guerrero, 2018) and whether the null hypothesis can be rejected if the *p* value is less than .05. The results of the statistical analysis for multiple logistic regression revealed the validity of the first hypothesis, regarding BOOST tool implementation and readmissions. Using multiple linear regression, I tested the second hypothesis, BOOST tool implementation and length of stay.

Multiple logistic regression is of use when the dependent variable is binary (Statistics Solutions, 2020). The dependent variable for the hypothesis in RQ 1 was readmissions, which was a binary variable with two categorical outcomes, (i.e., yes or no). The assumptions of logistic regression include a dichotomous dependent variable, a linear relationship between the odds ratio and the independent variable, absence of outliers in the data, and a large sample size (Statistics Solutions, 2020). In a logistic regression model, the Wald Chi-square tests the null hypothesis (Warner, 2013). For the hypothesis in RQ 1, the Wald Chi-square test under multiple logistic regression was of use, and a *p* value of .05 determined the statistical significance between BOOST tool implementation and readmissions. The Hosmer and Lemeshow goodness of fit test determines the model's fit with the significant *p* value (Statistics Solutions, 2020).

The assumptions of multiple linear regression include a linear relationship, multivariate normality, absence of multicollinearity, homoscedasticity, and an appropriate sample size of 20 cases per independent variable (Statistics Solutions, 2020). Multiple linear regression involves a linear relationship between the independent and dependent variables (Statistics Solutions, 2020). A scatter plot can be used to investigate the assumption of linearity (Statistics Solutions, 2020). Multiple linear regression assumes normal distribution with the residuals, which can be examined through a histogram or a goodness of fit test such as the Kolmogorov-Smirnov test (Statistics

Solutions, 2020). The Kolmogorov-Smirnov test is appropriate for sample sizes greater than 50 (Gerald, 2018). Another assumption is the absence of multicollinearity when independent variables are not highly correlated with one another (Statistics Solutions, 2020). Multicollinearity is examined by analyzing the variance inflation factor (VIF), where VIF values greater than 10 indicate variances are related to multicollinearity (Statistics Solutions, 2020). The assumption of homoscedasticity states that there is a similarity in variances between variables and a residual scatter plot can assess this distribution (Statistics Solutions, 2020). T tests are used to determine the impact of one variable on another variable (Gerald, 2018). The hypothesis in RQ 2 was tested by utilizing the *t* tests in multiple linear regression, and a *p* value of .05 was of use to determine the statistical significance between BOOST tool implementation and length of stay.

Threats to Validity

Internal Validity

For this quantitative study, the factors that posed a threat to internal validity include confounding elements and statistical regression (Creswell & Creswell, 2018). Confounding elements in this study included variances in practice, such as inconsistencies in documentation in the medical record. Such inconsistencies may lead to miscommunication and unaddressed needs within the BOOST tool prior to hospital discharge. A threat to statistical regression occurred due to lack of access to the dataset at the respondent-level for the Press Ganey surveys. I was unable to test the hypothesis in RQ 3, and therefore, a conclusion for RQ 3 cannot be drawn. Database comparison with the data extraction team, informatics and analytics team, and quality improvement department was used to address potential threats to systematic errors. Sample sepsis selection representing the population was utilized to improve the study's internal validity.

External Validity

A potential threat to external validity was generalizability, as the setting of this study was only one academic affiliated healthcare organization in the West Coast region of the United States. Utilizing one healthcare organization in one region may pose concerns for generalizability for the population sample. Threats to address construct validity included providing accurate definitions and measures of variables (Creswell & Creswell, 2018). For this quantitative study, each variable definition and measurement was outlined to avoid potential threats to external validity.

Ethical Procedures

IRB approval was obtained from the partner site and from Walden University. The Walden IRB approval number for this study is 08-04-21-0751692. After IRB approval from Walden University and the partner site, archival data came from the partner site with the assistance of the informatics and analytics team and the data extraction department. Informed consent forms were not necessary because this quantitative study involved de-identified secondary data analysis. I will store the data for 7 years, as required, in a secure, password protected hard drive. The archival data came from my place of employment. Additionally, I did not take part in the implementation of the BOOST tool project at the partner site. Finally, I am not a member of the quality improvement team or the analytics data extraction team of the site under study.

Summary

In Chapter 3, I provided a detailed description of the collection and data analysis plan for this quantitative study. Multiple logistic regression was used to test the first hypothesis regarding BOOST tool implementation and readmissions. Multiple linear regression was employed to test the second hypothesis centering on BOOST tool implementation and length of stay. The third hypothesis focusing on BOOST tool implementation and patient satisfaction was not tested and descriptive analysis without significance testing was used to evaluate the aggregated data for RQ 3. In this chapter, I discussed the operationalization of the independent variables, dependent variables, and control variables. The predictor variable was BOOST tool implementation. The outcome variables were readmissions and length of stay. Through this study, I investigated BOOST tool implementation and the relationship to readmissions and length of stay in patients with sepsis. Chapter 4 includes a detailed description of the data collection, discrepancies from the data collection described in Chapter 3, the results of the statistical analysis, and the conclusions of the hypothesis testing.

Chapter 4: Results

The purpose of this quantitative study was to investigate the relationship between BOOST tool implementation and hospital quality outcomes including readmissions, length of stay, and patient satisfaction in patients with sepsis, which the RQs were designed to answer. In this study, I evaluated the probability of 30-day hospital readmissions after BOOST tool implementation from the index (initial) sepsis admission. The probability that length of stay would decrease was evaluated based on the index (initial) sepsis admission when BOOST tool elements were implemented prior to discharge. Patient satisfaction scores from the Press Ganey discharge domain were reviewed. Due to the lack of access to the Press Ganey surveys at the respondent level, I was unable to test the hypothesis and therefore, I was unable to draw a conclusion for RQ 3 (BOOST tool implementation and patient satisfaction).

Time Frame and Archival Data Collection of Patients with Sepsis

Archival data were extracted by the informatics and analytics team from the electronic source at the partner site. Admission and readmission dates included January 2017 to June 2019 (before BOOST implementation) and July 2019 to April 2021 (after BOOST implementation). Patients ages 18 years and older, males and females, with a sepsis, severe sepsis, or septic shock diagnosis at index (initial) admission and at 30-day readmission were included in the dataset. Archival data consisted of documentation of BOOST tool elements that were addressed prior to hospital discharge, health insurance coverage, length of stay, and aggregated data from the Press Ganey patient satisfaction scores.

Descriptive Statistics

I used SPSS to obtain descriptive statistics and frequencies of the variables in this quantitative study. The total sample size for sepsis-related admissions was 1,409 between January 2017 to April 2021. Upon testing the logistic regression assumptions, 15 outliers were listed. I removed the 15 outliers, considering the large sample size. The actual sample size was 1,394 sepsis-related admissions.

From SPSS, the variables included in the descriptive statistics and frequencies table before BOOST tool implementation were age, gender, health insurance coverage, index (initial) diagnosis, length of stay, 30-day readmission, and BOOST tool implementation (Table 3). The descriptive statistics and frequencies included a total of 681 sepsis-related admissions between January 2017 to June 2019. Of these, most were sepsis admissions (557, 81.8%). The mean age for patients was 63.9 years. There were 288 (42.3%) females and 393 (57.7%) males. There were various types of health insurance coverage including Medicare, Medicaid/self-pay, and private insurance/other. Most had Medicare (49.5%), followed by 235 patients (34.5%) with private insurance/other. The length of stay ranged from 1 day to 219 days. There were 218 readmissions (32%) 30 days after a sepsis hospital discharge. Since the BOOST tool was not yet implemented, the values for this area were zero. There were no missing values in this dataset.

Table 3

Descriptive Statistics and Frequencies Before BOOST (January 2017–June 2019)

	Frequency	Percent	Mean	Min	Max	Range	SD
Age			63.87	19	103	84	20.294
Gender							
Female	288	42.3					
Male	393	57.7					
Total	681	100					
Diagnosis							
Sepsis	557	81.8					
Severe Sepsis	94	13.8					
Septic Shock	30	4.4					
Total	681	100					
Health Insurance Coverage							
Private Insurance/Other	235	34.5					
Medicaid/Self-Pay	109	16.0					
Medicare	337	49.5					
Total	681	100					
Readmissions							
No 30-Day Readmission	463	68.0					
30-Day Readmission	218	32.0					
Total	681	100					
Length of Stay			8.79	1	219	218	14.464

The variables included in the descriptive statistics and frequencies table after BOOST tool implementation were age, gender, health insurance coverage, index (initial) diagnosis, length of stay, 30-day readmission, and BOOST tool implementation (Table 4). There were 713 sepsis-related admissions, with 652 (91.4%) being sepsis admissions, and 27 (3.8%) septic shock admissions. Again, the mean age was 63.9 years old. There were 348 (48.8%) females and 365 (51.2%) males. Again, health insurance coverage included Medicare, Medicaid/self-pay, and private insurance/other. Most had Medicare (358, 50.2%). The length of stay ranged from 1 day to 124 days. There were 232 readmissions (32.5%) 30 days after a sepsis hospital discharge. BOOST tool documentation was completed in 195 (27%) cases. There were no missing values in this dataset.

Table 4

Descriptive Statistics and Frequencies After BOOST (July 2019–April 2021)

	Frequency	Percent	Mean	Min	Max	Range	SD
Age			63.97	18	105	87	19.486
Gender							
Female	348	48.8					
Male	365	51.2					
Total	713	100					
Diagnosis							
Sepsis	652	91.4					
Severe Sepsis	34	4.8					
Septic Shock	27	3.8					
Total	713	100					
Health Insurance Coverage							
Private Insurance/Other	233	32.7					
Medicaid/Self-Pay	122	17.1					
Medicare	358	50.2					
Total	713	100					
Readmissions							
No 30-Day Readmission	481	67.5					
30-Day Readmission	232	32.5					
Total	713	100					
Length of Stay			9.80	1	124	123	13.394
Before/After BOOST Tool Documented (July 2019-April 2021)	195	27					
Not Documented (July 2019-April 2021)	518	73					
Total	713	100					

The variables included in the descriptive statistics and frequencies table for all admissions from January 2017 to April 2021 were age, gender, health insurance coverage, index (initial) diagnosis, length of stay, 30-day readmission, and BOOST tool implementation (Table 5). The descriptive statistics and frequencies included a total of 1,394 sepsis-related admissions between January 2017 to April 2021. Of these, 1,209 (86.7%) were sepsis admissions. The mean age was again 63.9 years old, and there were 636 (45.6%) females and 758 (54.4%) males. Health insurance coverage included Medicare, Medicaid/self-pay, and private insurance/other. Like other datasets, most had Medicare (692, 49.6%), followed by private insurance/other (469, 33.7%). The mean length of stay was 9.30 days. There were 450 readmissions (32.3%) 30 days after a sepsis hospital discharge. BOOST tool documentation was completed in 195 (27%) cases. There were no missing values in this dataset.

Table 5

Descriptive Statistics and Frequencies for All Admissions (January 2017–April 2021)

	Frequency	Percent	Mean	Min	Max	Range	SD
Age			63.92	18	105	87	19.878
Gender							
Female	636	45.6					
Male	758	54.4					
Total	1394	100					
Diagnosis							
Sepsis	1209	86.7					
Severe Sepsis	128	9.2					
Septic Shock	57	4.1					
Total	1394	100					
Health Insurance Coverage							
Private Insurance/Other	469	33.7					
Medicaid/Self-Pay	233	16.7					
Medicare	692	49.6					
Total	1394	100					
Readmissions							
No 30-Day Readmission	944	67.7					
30-Day Readmission	450	32.3					
Total	1394	100					
Length of Stay			9.30	1	219	218	13.931
Before/After BOOST Tool							
Documented (July 2019-April 2021)	195	27					
Not Documented (July 2019-April 2021)	518	73					
Total	713	100					

Statistical Assumptions

Statistical assumptions were tested to determine whether the assumptions were violated or met. The assumptions of multiple logistic regression include a dichotomous dependent variable, a linear relationship between the odds ratio and the independent variable, no outliers in the data, absence of multicollinearity amongst the independent variables, and a large sample size (Statistics Solutions, 2020). The assumptions of multiple linear regression include a linear relationship, multivariate normality, absence of multicollinearity, homoscedasticity, and an appropriate sample size of 20 cases per independent variable (Statistics Solutions, 2020).

Testing Logistic Regression Assumptions for RQ 1 (BOOST Tool and Readmissions)

The logistic regression assumptions for RQ 1 were tested in SPSS. In RQ 1 (BOOST tool implementation and readmissions), the dependent variable was readmissions, which is binary with a yes/no outcome. Therefore, this assumption was met. The assumption of no multicollinearity for January 2017 to April 2021 resulted in values greater than 0.1 (Appendix G, Table G1); therefore, this assumption was met. There were 15 outliers in the Casewise List with a ZResid (standardized residual) value greater than 2.5. Since the total sample size was large (1,409), I removed the 15 outliers from the dataset (Appendix G, Table G2). After I removed the 15 outliers, I searched for outliers again and there were no outliers, indicating that the assumption of the absence of outliers was met.

Testing Linear Regression Assumptions for RQ 2 (BOOST Tool and Length of Stay)

There are several assumptions in multiple linear regression including linearity, normal distribution, absence of multicollinearity, and homoscedasticity (Statistics Solutions, 2020). Multiple linear regression requires a linear relationship between the dependent and independent variables (Statistic Solutions, 2020). A scatter plot can be used to investigate the assumption of linearity (Statistics Solutions, 2020). Multiple linear regression assumes normal distribution with the residuals, which can be examined through a histogram (Statistic Solutions, 2020). Multicollinearity is examined by analyzing the VIF, where VIF values greater than 10 indicate variances are related to multicollinearity (Statistics Solutions, 2020). The assumption of homoscedasticity states that there is a similarity in variances between variables and a residual scatter plot can assess this distribution (Statistics Solutions, 2020).

In SPSS, the dataset for length of stay did not show a linear pattern in the P-P (predicted probability) plot (Appendix H, Figure H1), which indicated that the assumption of linearity was violated for the dependent variable, length of stay. To amend the violation for the assumption of linearity, I used log transformation to allow for normal distribution. After log transformation, the linear pattern (Appendix H, Figure H2) indicated that the assumption for linearity was met for the dependent variable, length of stay.

In SPSS, I used the histogram to test the assumption of normal distribution. The dependent variable, length of stay, was positively skewed (Appendix H, Figure H3). To amend the violation for the assumption of normal distribution, I used log transformation to allow for normal distribution. The skewness value was 0.538 (Appendix H, Table H1) after log transformation. After log transformation, the histogram showed an evenly distributed pattern (Appendix H, Figure H4), which indicated that the assumption of normal distribution was met for the dependent variable, length of stay.

In SPSS, I used Pearson Correlation to test the assumption of the absence of multicollinearity. The values for age, gender, insurance coverage, and diagnosis were greater than 0.1. The VIF was less than 10, which indicated that there was no multicollinearity. The assumption of the absence of multicollinearity was met for the dependent variable, length of stay.

I used the scatterplot in SPSS to test the assumption of homoscedasticity. The scatterplot showed a clustered pattern (Appendix H, Figure H5), which indicated that the assumption of homoscedasticity was violated for the dependent variable, length of stay. To amend this violation, I used log transformation to allow for distribution. After log transformation, the scatterplot showed a scattered pattern (Appendix H, Figure H6), which indicated that the assumption for homoscedasticity was met.

Results

Results for BOOST Tool Implementation and Readmissions (RQ 1)

In SPSS, I used binary logistic regression to investigate the relationship between BOOST tool implementation and 30-day readmissions and to determine whether the covariates (age, gender, health insurance coverage, and disease state) were associated with the likelihood of 30-day readmissions in the sepsis population. The Hosmer and Lemeshow Test indicated p = .055, which was higher than .05, indicating that the model was a good fit for the dataset. Results for RQ 1 indicated that there was no statistically significant relationship between BOOST tool implementation and readmissions.

There was no statistically significant relationship between BOOST tool implementation (p = .884) and readmissions (Table 6). Therefore, the null hypothesis in RQ 1 was accepted. The covariates age (p = .014) and the diagnosis of severe sepsis (p = .006) had a statistically significant relationship with readmissions (Table 6). Based on my review of the descriptive statistics and frequencies, the 30-day readmission rate for the sepsis population was 32% before BOOST tool implementation. After BOOST tool implementation, the 30-day readmission rate for the sepsis population was 32.5%. From the descriptive statistics and frequencies, there was a 0.5% increase in readmissions in the sepsis population after BOOST tool implementation.

Table 6

Logistic Regression Predicting the Likelihood of 30-Day Readmissions in Sepsis Patients

	B	SE	Wald	df	Sig.	Exp (B) (Odds Ratio)	95% C.I. for Exp (B)	
							Lower	Upper
Age	-.008	.003	6.014	1	.014	.992	.985	.998
Gender	.072	.117	.376	1	.540	1.074	.854	1.351
Insurance Coverage			2.064	2	.356			
Severe Sepsis Diagnosis	-.954	.349	7.477	1	.006	.385	.194	.763
Before/ After BOOST Tool	.017	.117	.021	1	.884	1.017	.809	1.280

Results for BOOST Tool Implementation and Length of Stay (RQ 2)

In SPSS, I conducted a multiple linear regression analysis using the enter method to examine the relationship between BOOST tool implementation and length of stay and to determine whether the covariates age, gender, health insurance coverage, and disease state were associated with the likelihood of decreased length of hospital stays in the sepsis population. Results for RQ 2 indicated that there was a statistically significant relationship between BOOST tool implementation (p = .014) and length of stay (Table 7). Therefore, the null hypothesis was rejected. BOOST tool implementation (p = .014) had a coefficient of .051, which indicated that there was a .05% higher length of stay after BOOST implementation. There was a statistically significant relationship between BOOST tool implementation and the covariates age (p = .001), insurance coverage (p = .047), and the index (initial) diagnosis of severe sepsis (p = .009). In my review of the descriptive statistics and frequencies, the average length of stay before BOOST tool implementation was 8.79 days. After BOOST tool implementation, the average length of stay was 9.80 days. Based on the descriptive statistics and frequencies, there was an increase by 1.01 days in length of stay after BOOST tool implementation for the sepsis population at the partner site.

Table 7

Coefficients[a] Table for Length of Stay

	Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% CI for B	
						Lower	Upper
Age	-.002	.001	-.099	-3.230	.001	-.003	-.001
Gender	.007	.021	.008	.317	.751	-.034	.047

Insurance Coverage	.026	.013	.060	1.988	.047	.000	.051
Severe Sepsis Diagnosis	.057	.022	.070	2.614	.009	.014	.099
Before/After BOOST Tool	.051	.021	.066	2.462	.014	.010	.091

a. Dependent Variable: Log10_Length of Stay

Results for BOOST Tool Implementation and Patient Satisfaction (RQ 3)

Press Ganey sepsis patient satisfaction scores were extracted by the informatics and analytics team at the partner site. There were 689 sepsis respondents between 2017 to 2021. Table 8 includes the Press Ganey aggregated data for diagnostic related groups pertaining to the sepsis population, including septicemia or severe sepsis with mechanical ventilation, septicemia or severe sepsis without mechanical ventilation greater than 96 hours with major complications/comorbidities, and septicemia or severe sepsis without mechanical ventilation greater than 96 hours without major complications/comorbidities. Press Ganey uses a Likert scale for each survey question with the following ratings: *Very Poor* = 1, *Poor* = 2, *Fair* = 3, *Good* = 4, *Very Good* = 5. Press Ganey then converts the ratings to a mean score on a scale of 0-100 for each answer. A mean score is the arithmetic average that represents the respondents' answers to the survey questions.

The five discharge domain questions listed in Table 8 includes (a) extent the patient felt ready for discharge, (b) speed of the discharge process, (c) instructions for care at home, (d) explanation on taking the medicine after discharge, and (e) case manager assistance with the discharge plan. Before BOOST tool implementation, the mean score for patient's readiness for discharge was 86.70, speed of the discharge process was 79.42, instructions for care at home was 86.07, explanation about medications after discharge was 84.81, case manager assistance with the discharge plan was 81.41, and patient satisfaction score for overall discharge was 83.25. After BOOST tool implementation, the mean scores were 87.81, 80.02, 86.61, 87.41, 86.36, and 84.96. Since I was unable to test the hypothesis in RQ 3, a conclusion cannot be drawn based on simple descriptive analysis of the aggregated data from the Press Ganey patient satisfaction scores.

Table 8

Press Ganey Aggregated Data (Before and After BOOST)

Year	Discharge Domain Questions	Mean	*n*
January 2017-June 2019 (Before BOOST)	Extent felt ready for discharge	86.70	389
	Speed of discharge process	79.42	385
	Instructions for care at home	86.07	377
	Explanation on taking medicine after discharge	84.81	135
	Case manager assistance with discharge plan	81.41	355
Discharge Overall		83.25	398
July 2019-April 2021 (After BOOST)	Extent felt ready for discharge	87.81	285
	Speed of discharge process	80.02	284
	Instructions for care at home	86.61	280
	Explanation on taking medicine after discharge	87.41	141
	Case manager assistance with discharge plan	86.36	88
Discharge Overall		84.96	291

Summary

The assumptions for RQ 1 and RQ 2 were tested prior to hypothesis testing to determine whether the assumptions were met or violated. In RQ 1, the assumptions of multiple logistic regression were met. There were 15 outliers in the Casewise list, which were removed since there was a large sample size of 1,409. The actual total sample size was 1,394 after the outliers were removed. There were no missing values in the dataset from January 2017 to April 2021. In RQ 2, the assumptions of normality, linearity, and homoscedasticity for multiple linear regression were violated. To amend the violations, I used log transformation to allow for normal distribution and the assumptions were met.

An analysis was conducted in RQ 1 and RQ 2 to determine the statistical significance between BOOST tool implementation, readmissions, and length of stay. In RQ 1, the null hypothesis was accepted because there was no statistically significant relationship between BOOST tool implementation (p = .884) and the likelihood of hospital readmissions for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state. Based on a review of the descriptive statistics and frequencies, there was a 0.5% increase in readmissions after BOOST tool implementation at the partner site. In RQ 2, the null hypothesis was rejected because there was a statistically significant relationship between BOOST tool implementation (p = .014) and average length of stay for patients with sepsis adjusting for age, gender, health insurance coverage, and disease state. BOOST tool implementation was associated with a .05% higher length of stay. Based on a review of the descriptive statistics and frequencies, there was an increase by 1.01 days in length of stay after BOOST tool implementation for the sepsis population at the partner site.

In Chapter 5, I discuss the conclusions of this quantitative study. I describe my interpretation of the findings as well as the limitations and my recommendations for further research. Finally, I discuss the potential impact for positive social change as a result of this study.

Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this quantitative study was to investigate the relationship between BOOST tool implementation and readmissions, length of stay, and patient satisfaction in the sepsis population. The nature of this study was a quantitative analysis with the use of multiple logistic regression and multiple linear regression. I obtained secondary data from the partner site, which was an 800-bed, acute care hospital, located in the West Coast region of the United States. The target population for this study included hospitalized males and females, 18 and older, admitted and readmitted within 30 days with a sepsis, severe sepsis, or septic shock diagnosis from January 2017 to April 2021. The years January 2017 to June 2019 are before BOOST implementation period and the years July 2019 to April 2021 are after BOOST implementation period, which was used to assess statistical significance before and after BOOST tool implementation and readmissions and length of stay in the sepsis population. The independent variable was BOOST tool implementation. The dependent variables were readmissions and length of stay. The control variables were age, gender, health insurance coverage, and disease state. The sample size consisted of 1,394 sepsis patients who met inclusion criteria. My research showed statistical significance in the relationship between BOOST tool implementation ($p = .014$) and length of stay. There was no statistically significant relationship between BOOST tool implementation ($p = .884$) and readmissions.

I used multiple logistic regression to test the hypothesis in RQs 1 and 2. I initially proposed to use multiple linear regression to test the hypothesis in RQ 3, but due to not being able to obtain the data set, I conducted a simple descriptive analysis without significance testing for RQ 3. In RQ 1, there was no statistically significant relationship between BOOST tool implementation (*p* = .884) and readmissions. Therefore, the null hypothesis was accepted. In RQ 2, there was a statistically significant relationship between BOOST tool implementation (*p* = .014) and length of stay. Therefore, the null hypothesis was rejected. In RQ 3, a conclusion could not be drawn based on descriptive analysis of the Press Ganey aggregated data. Therefore, further investigation is needed in this area. An analysis of the patient-level surveys is needed to determine whether patient satisfaction scores improved after BOOST tool implementation.

Interpretation of the Findings

Risk stratification tools such as the BOOST tool were created to reduce unnecessary readmissions, decrease hospital length of stays, and improve patient health outcomes. Based on the literature review, I expected the implementation of the BOOST tool to reduce readmissions and decrease length of hospital stays. However, based on my findings, implementation of the BOOST tool at the partner site did not reduce readmissions or shorten length of stay for the sepsis population.

In RQ 1, I did not find a statistically significant relationship between BOOST tool implementation (*p* = .884) and 30-day readmissions. In contrast to my study, researchers such as Hansen et al. (2013) discovered that the application of the BOOST tool in 11 U.S. hospitals decreased readmissions by 2% among medical surgical patients. Similarly, Lee et al. (2016) reported that the BOOST tool predicted 90% of readmissions when risk factors were utilized. Additionally, Sieck et al. (2019) cited that the risk factors listed in the BOOST tool were associated with hospital readmissions. From the descriptive statistics and frequencies, there was a 0.5% increase in readmissions in the sepsis population after BOOST tool implementation at the partner site. Considering the BOOST tool was implemented in every electronic inpatient chart, I expected a high BOOST tool completion rate (i.e., closer to 100%) and a reduction in readmission rates. However, based on my review of the descriptive statistics and frequencies, the BOOST tool completion rate was low at 27%, which could have impacted the readmission rate results. The BOOST tool was designed to avoid missed opportunities for intervention prior to hospital discharge. Therefore, a critical factor in readmission reduction includes addressing the evidence-based elements and best practices listed within the BOOST tool prior to hospital discharge. External factors that may have impacted BOOST tool completion include staffing shortage related to the COVID-19 pandemic in 2020–2021. Further investigation is needed in this area to determine whether staffing shortage affected BOOST tool completion rates.

In RQ 2, I found a statistical significance in the relationship between BOOST tool implementation (p = .014) and length of stay. I found a .05% higher length of stay after BOOST implementation. In my review of the descriptive statistics and frequencies, there was an increase by 1.01 days in length of stay after BOOST tool implementation for the sepsis population at the partner site. In contrast to my study, Hansen et al. (2013) found that length of stay decreased by 0.5 days after BOOST implementation in medical-surgical units. Conversely, Johnson et al. (2021) did not find a statistically significant relationship in length of stay and BOOST tool when applied to inpatient mobility on a general medicine unit. Similar to RQ 1, I expected a higher completion rate (i.e., closer to

100%) and a decrease in length of hospital stay. Factors to consider in the low BOOST tool completion rate are short staffing and severity of illness. Severity of illness is a key aspect in analyzing length of stay. For this study, the diagnoses of sepsis, severe sepsis, and septic shock were categorical variables. As an indicator of severity, these disease state variables can also be ordinal variables. As the biological nature of sepsis progresses, the intensity of hospital interventions may also increase, which may require longer length of hospital stays. Hospital interventions such as intravenous antibiotics may prolong the hospital course for the sepsis population. Therefore, severity of illness and intensity of hospital service may have also impacted the results in RQ 2.

In RQ 3, I reviewed the Press Ganey sepsis aggregated data, which indicated a mean patient satisfaction score of 83.25 for overall discharge before BOOST tool implementation. After BOOST tool implementation, the mean patient satisfaction score was 84.96 for overall discharge. Prior researchers such as Wang et al. (2015) and Figueroa et al. (2018) conducted studies on discharge planning and patient satisfaction. Wang et al. found a positive relationship between care coordination, discharge planning, and patient satisfaction. The odds ratio for overall care coordination and patient satisfaction was 1.78. Further, Figueroa et al. reported that hospitals experienced high patient satisfaction scores when they provided discharge summaries, medication education, discharge coordinators, and follow-up phone calls 48 hours post discharge. Without hypothesis testing, I was unable to draw a conclusion based on descriptive analysis from the Press Ganey aggregated data. Further investigation is needed in this area to determine whether patient satisfaction scores improved after BOOST tool implementation.

For this quantitative study, relational coordination theory was the theoretical framework applied to the RQs. In RQ 1 and RQ 2, the assessment of the relationship between BOOST tool implementation, readmissions, and length of stay occurred, where the BOOST tool fell under the relational coordination category and readmissions and length of stay fell under quality in the performance category of the relational coordination model. Relational coordination theory is applicable in this study because of the focus on quality measures as listed within the evidence-based elements in the BOOST tool. Evidence-based elements within the BOOST tool that reflect quality of care include standardization of practices in sepsis discharge preparation and patient/caregiver education in sepsis self-care to improve health literacy and promotion of health and well-being.

Limitations of the Study

There were several limitations in this quantitative study. The limitations included low generalizability, confounding factors such as inconsistencies in practice on BOOST tool documentation, and lack of access at the respondent level for the patient satisfaction surveys during data collection. My study focused on one acute care hospital, adult patients only with a sepsis, severe sepsis, or septic shock diagnosis. Therefore, the results of this study cannot be used to generalize the impact on subacute or specialty hospitals, the pediatrics population, or other medical conditions except for those that are sepsis-related.

Methodological weaknesses include confounding factors such as lack of compliance in BOOST tool completion as evidenced by the low completion rate at 27% between the years 2019–2021 for the sepsis population at the partner site. Staffing shortage related to the COVID-19 pandemic may have contributed to the low BOOST tool completion rate. Further investigation is needed to determine whether staffing shortage was related to low BOOST tool completion rates. Other confounding factors included patients who have expired, patients who left the hospital against medical advice, and patients who were not readmitted to the partner site for this study. Patients who have expired or left against medical advice were still included in the study if they had a record of an index (initial) sepsis admission, and/or a 30-day sepsis readmission after a hospital discharge, which was a reasonable measure to address this limitation. Additional confounding factors include lack of access to the respondent-level data. During the data collection phase, the informatics and analytics team were unable to provide the dataset at the respondent-level for the Press Ganey patient satisfaction surveys. Therefore, hypothesis testing was not conducted and I was unable to draw a conclusion for RQ 3 (BOOST tool implementation and patient satisfaction).

Recommendations for Further Research

Based on my research findings, I would recommend further investigation in the consistency of team documentation within the BOOST tool. The aggregated data from the partner site showed that the BOOST tool was implemented on 27% of the sepsis population prior to hospital discharge, which indicated opportunities for improvement in BOOST tool implementation prior to discharge. Further research is needed to investigate standardization of practice in this area. Although the BOOST tool was designed to decrease readmissions and length of stays, my findings indicated no statistical significance in BOOST tool implementation and readmissions. I also found an increase in readmissions and length of stays for the sepsis population after BOOST implementation. Further investigation is recommended to potentially apply an alternative tool to monitor readmissions and length of stays for the sepsis population.

I expected an improvement in patient satisfaction scores after BOOST tool implementation. Since I was unable to test the hypothesis in RQ 3 (BOOST tool implementation and patient satisfaction), further research is needed as I was unable to draw a conclusion based on descriptive analysis. Further research is needed in this area because patient satisfaction scores with the best-practice elements in the BOOST tool may reveal opportunities for improvement in quality of care.

Implications

Healthcare organizations continue to monitor hospital quality outcome measures through predictor models and risk stratification tools to reduce readmissions, decrease length of stay, and improve patient satisfaction. The BOOST tool is still applicable to the sepsis population because it includes the evidence-based elements and best practices that can improve quality of patient care. Evidence-based practices listed in the BOOST tool could lead to the following positive outcomes: (a) standardized practices in sepsis discharge preparation, (b) empowerment of patients and caregivers in sepsis self-care, (c) improved health literacy in sepsis disease management and prevention to promote health and well-being, and (d) improved quality of life in the sepsis population. Findings from this study may contribute to positive social change through the optimization of sepsis care coordination and standardized discharge planning for this patient population. Implications for professional practice may provide practical application for clinicians, lawmakers, and insurance payors by implementing best practices in care coordination and reimbursement guidelines for patients with sepsis. My findings may lead to the implementation of an alternative tool to monitor readmissions and length of stays in the sepsis population.

Conclusion

Sepsis is a global concern because it contributes to high mortality rates, increased healthcare cost, and poor patient outcomes. Healthcare organizations use risk stratification tools such as the BOOST tool to measure hospital quality outcomes including readmissions, length of stay, and patient satisfaction to improve quality of care. Through this quantitative study, I addressed the gap in literature by comparing the data before and after BOOST tool implementation to determine whether readmissions and length of stay decreased in the sepsis population.

I did not find statistical significance between BOOST tool implementation and readmissions. However, I found a statistical significance between the covariates age, the severe sepsis diagnosis, and readmissions. Additionally, I found a statistical significance between BOOST tool implementation and length of stay. I also found a statistical significance between BOOST tool implementation and the covariates age, insurance coverage, and the severe sepsis diagnosis.

Finally, my findings did not indicate a reduction in readmissions or a decrease in length of stay after BOOST tool implementation for the sepsis population. An alternative tool to monitor readmissions and length of stay in the sepsis population is recommended for future research. The evidence-based best practices listed within the BOOST tool can still be applied to the sepsis population to standardize quality of care practices such as health literacy in sepsis disease management and prevention, promotion of health and well-being, and improved quality of life.

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Appendix A: Permission to use the 8P Screening BOOST Tool for dissertation project

From: Education [redacted]

Sent: Thursday, June 4, 2020 1:08 PM

To: Jane Venus-Nocentelli [redacted] Education [redacted]

Subject: RE: Permission to use the 8P Screening BOOST Tool for dissertation project

Hi Jane, Yes, you may print/reference the tool provided 1.) the appropriate citations are used in your dissertation and 2.) it is not used for any revenue producing/seeking purposes at a later time.

Kind Regards,

Nick

From: Jane Venus-Nocentelli [redacted]

Sent: Wednesday, June 3, 2020 5:14 PM

To: Education [redacted]

Subject: Permission to use the 8P Screening BOOST Tool for dissertation project

Hello,

I am Jane Venus-Nocentelli, currently a doctoral student at Walden University. I am seeking permission to print the 8P Screening BOOST tool created by the Society of Hospital Medicine to include in my dissertation on the utilization of the BOOST tool in sepsis readmission reduction. Please provide guidance. Thank you so much.

Appendix B: Permission to Reprint the Model of Relational Coordination (Email)

From: Jody Hoffer Gittell [redacted]
Sent: Sunday, March 7, 2021 10:27 PM
To: Jane Venus-Nocentelli [redacted]
Subject: Re: Doctoral student requesting permission

That's great. Thank you and best wishes!

Jody Hoffer Gittell
Professor, The Heller School for Social Policy & Management, Brandeis University

Co-Founder and Board Member, Relational Coordination Collaborative
[redacted]

On Mar 7, 2021, at 2:09 PM, Jane Venus-Nocentelli [redacted] wrote:

Thank you so much, Dr. Gittell. For referencing in APA 7 format for the illustration will be referenced this way:

Above the figure,
Figure 1. Model of relational co-ordination. From "Organizing work to support relational co-ordination," by J.H. Gittell, 2000, *International Journal of Human Resource Management*, 11(3), p. 519.
Note. Reprinted with permission from Jody Hoffer Gittell

In the reference list, this is the format for the illustration:
Gittell, J. H. (2000). *Model of relational coordination*. From "Organizing work to support relational coordination." *International Journal of Human Resource Management, 11*(3), p. 519.

https://doi.org/10.1080/095851900339747

In the reference list, this is the format for the theory:
Gittell, J. H. (2000). Organizing work to support relational coordination. *International Journal of Human Resource Management*, *11*(3), 517-539. https://doi.org/10.1080/095851900339747

From: Jody Hoffer Gittell [redacted]
Sent: Saturday, March 6, 2021 11:21 AM

To: Jane Venus-Nocentelli [redacted]
Subject: Re: Doctoral student requesting permission
Dear Jane--

Thank you for writing and for your interest in relational coordination theory. Yes you have my permission to print an illustration of the model. Please let me know how you intend to reference the illustration and the theory in your list of references.

Jody

Jody Hoffer Gittell
Professor, The Heller School for Social Policy & Management, Brandeis University

Co-Founder and Board Member, Relational Coordination Collaborative

[redacted]

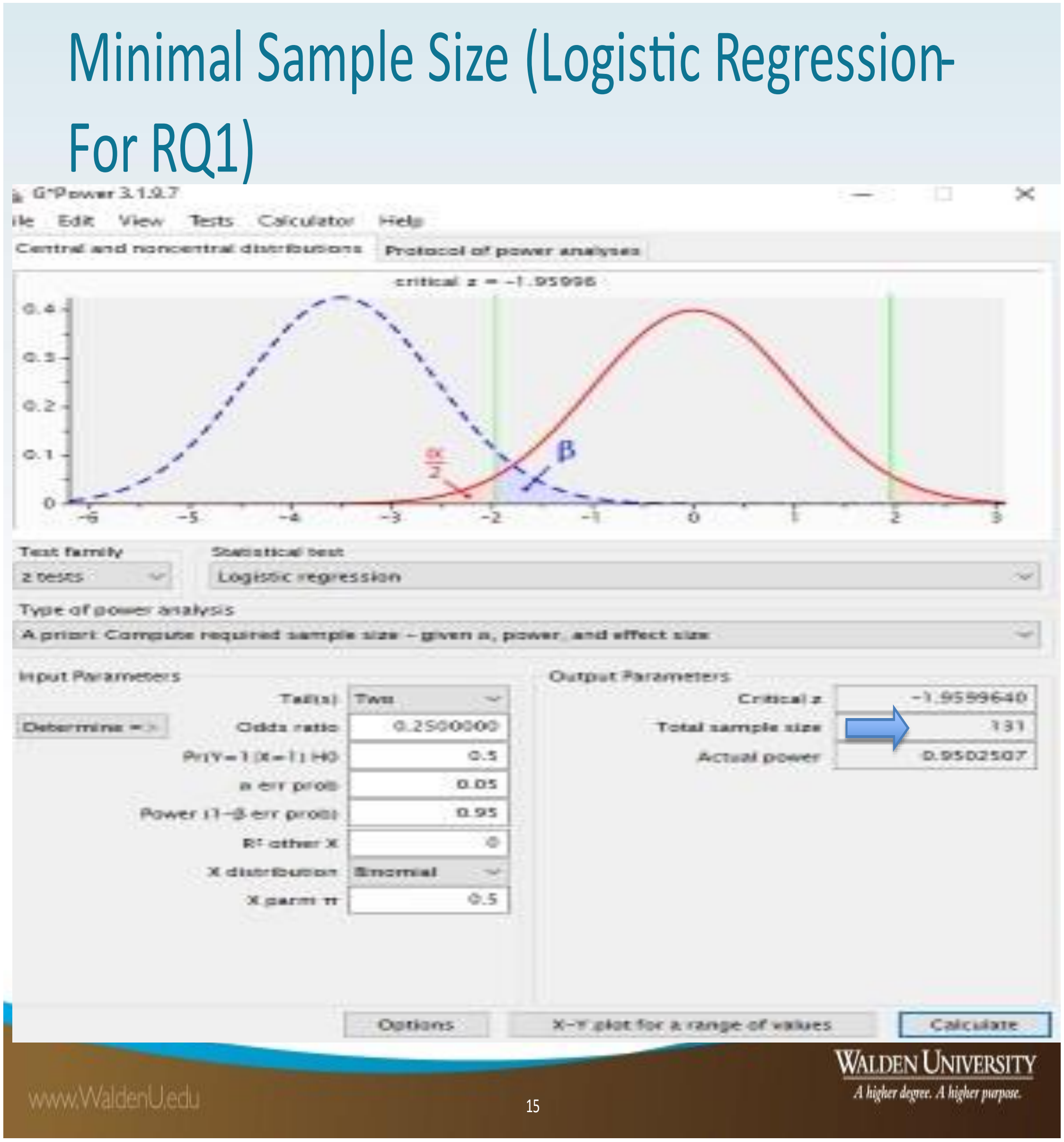
On Sat, Mar 6, 2021 at 2:10 PM Jane Venus-Nocentelli [redacted]> wrote:

Hi Dr. Gittell,

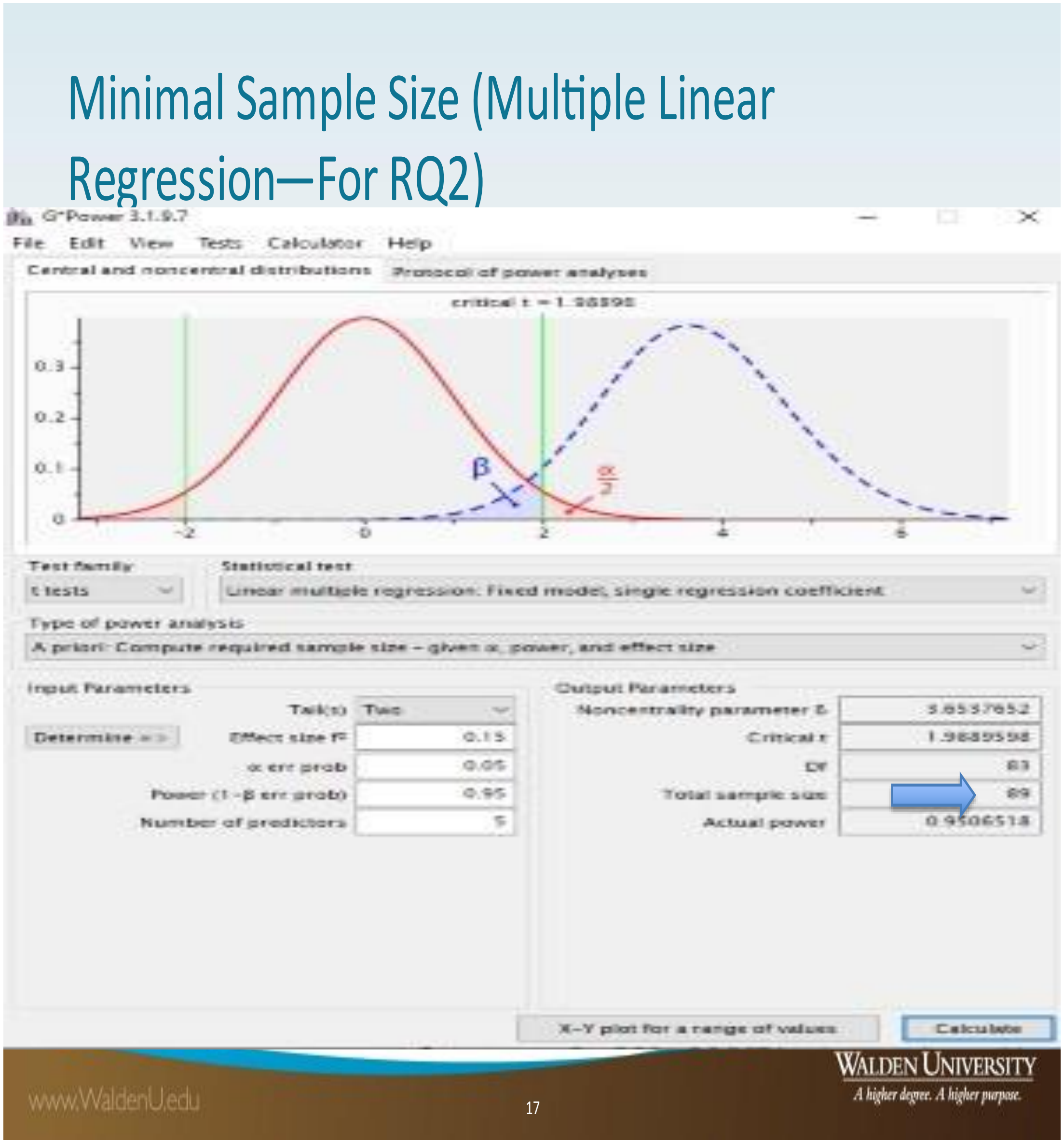
I am a doctoral student at Walden University and currently working on my proposal. I found your model of Relational Coordination to be in alignment with my study on sepsis patients and BOOST tool implementation. The BOOST tool contains multidisciplinary interventions to prevent hospital readmissions. I am requesting for permission to print the relational coordination model in my dissertation. Hoping for your kind consideration.

Sincerely,
Jane Venus-Nocentelli
Walden University Doctoral Candidate

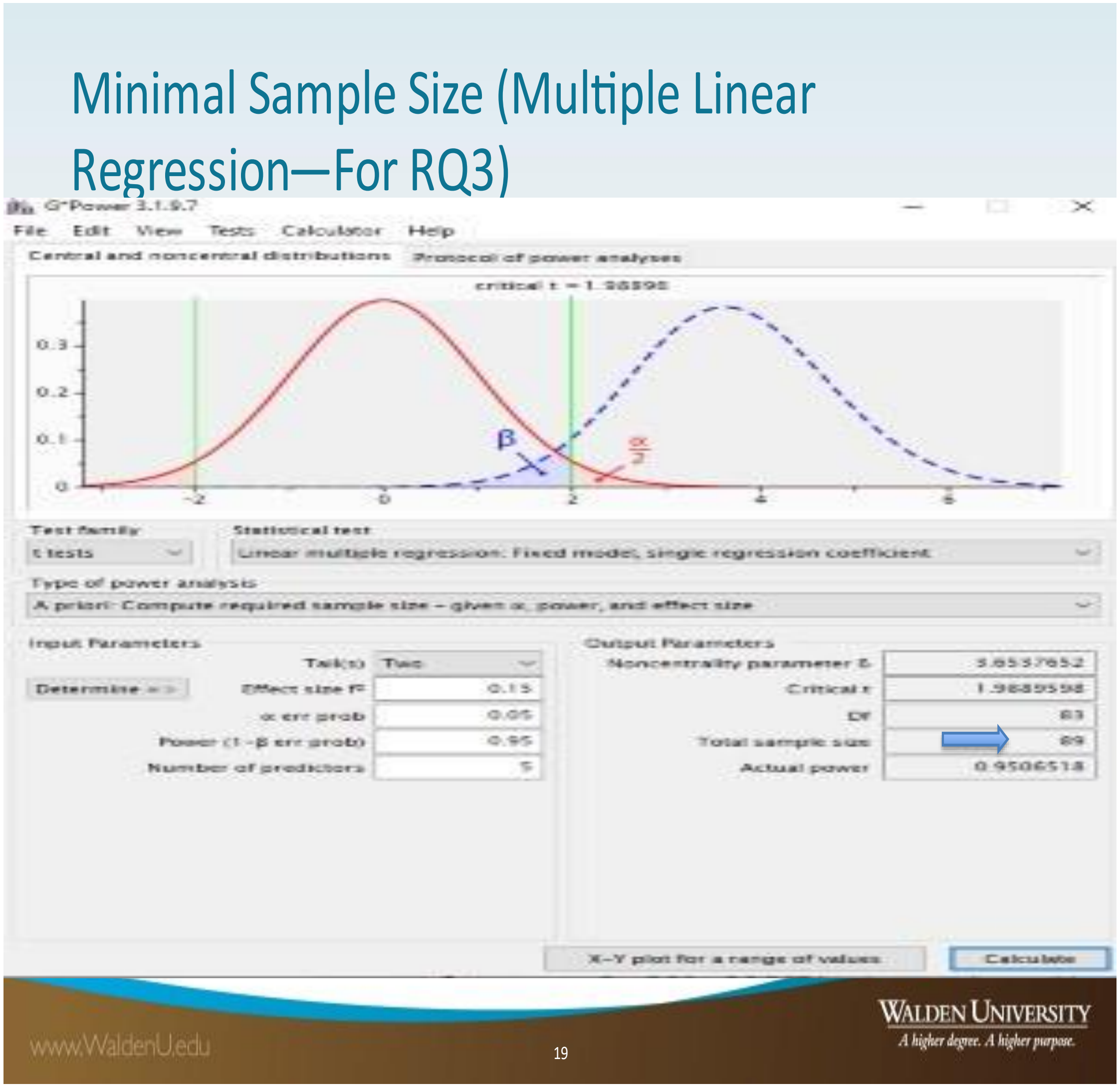
Appendix C: G* Power Sample Calculation for RQ 1



Appendix D: G* Power Sample Calculation for RQ 2



Appendix E: G* Power Sample Calculation for RQ 3



Appendix F: Press Ganey Questionnaire

SURVEY INSTRUCTIONS: You should only fill out this survey if you were the patient during the hospital stay named in the cover letter. Do not fill out this survey if you were not the patient. Answer all the questions by completely filling in the circle to the left of your answer. You are sometimes told to skip over some questions in this survey. When this happens you will see an arrow with a note that tells you what question to answer next, like this:

○ Yes

● No → ***If No, Go to Question 1***

Questions 1-19 and 23-29 are part of the HCAHPS Survey and are works of the U.S. Government. These HCAHPS questions are in the public domain and therefore are NOT subject to U.S. copyright laws. The three Care Transitions Measure® questions (Questions 20-22) are copyright of Eric A. Coleman, MD, MPH, all rights reserved.

PRESS GANEY®

SAMPLE

YOUR CARE FROM NURSES

1. During this hospital stay, how often did nurses treat you with courtesy and respect?
   - ○ Never
   - ○ Sometimes
   - ○ Usually
   - ○ Always
2. During this hospital stay, how often did nurses listen carefully to you?
   - ○ Never
   - ○ Sometimes
   - ○ Usually
   - ○ Always
3. During this hospital stay, how often did nurses explain things in a way you could understand?
   - ○ Never
   - ○ Sometimes
   - ○ Usually
   - ○ Always
4. During this hospital stay, after you pressed the call button, how often did you get help as soon as you wanted it?
   - ○ Never
   - ○ Sometimes
   - ○ Usually
   - ○ Always
   - ○ I never pressed the call button

YOUR CARE FROM DOCTORS

5. During this hospital stay, how often did doctors treat you with courtesy and respect?
   - ○ Never
   - ○ Sometimes
   - ○ Usually
   - ○ Always
6. During this hospital stay, how often did doctors listen carefully to you?
   - ○ Never
   - ○ Sometimes
   - ○ Usually
   - ○ Always
7. During this hospital stay, how often did doctors explain things in a way you could understand?
   - ○ Never
   - ○ Sometimes
   - ○ Usually
   - ○ Always

THE HOSPITAL ENVIRONMENT

8. During this hospital stay, how often were your room and bathroom kept clean?
   - ○ Never
   - ○ Sometimes
   - ○ Usually
   - ○ Always
9. During this hospital stay, how often was the area around your room quiet at night?
   - ○ Never
   - ○ Sometimes
   - ○ Usually
   - ○ Always

YOUR EXPERIENCES IN THIS HOSPITAL

10. During this hospital stay, did you need help from nurses or other hospital staff in getting to the bathroom or in using a bedpan?
    - ○ Yes
    - ○ No → **If No, Go to Question 12**
11. How often did you get help in getting to the bathroom or in using a bedpan as soon as you wanted?
    - ○ Never
    - ○ Sometimes
    - ○ Usually
    - ○ Always
12. During this hospital stay, were you given any medicine that you had not taken before?
    - ○ Yes
    - ○ No → **If No, Go to Question 15**

continue to page 2

Return To: Press Ganey Associates, 710 Rush Street, South Bend, IN 46601

13. Before giving you any new medicine, how often did hospital staff tell you what the medicine was for?
    - ◯ Never
    - ◯ Sometimes
    - ◯ Usually
    - ◯ Always

14. Before giving you any new medicine, how often did hospital staff describe possible side effects in a way you could understand?
    - ◯ Never
    - ◯ Sometimes
    - ◯ Usually
    - ◯ Always

WHEN YOU LEFT THE HOSPITAL

15. After you left the hospital, did you go directly to your own home, to someone else's home, or to another health facility?
    - ◯ Own home
    - ◯ Someone else's home
    - ◯ Another health facility → **If Another, Go to Question 18**

16. During this hospital stay, did doctors, nurses or other hospital staff talk with you about whether you would have the help you needed when you left the hospital?
    - ◯ Yes
    - ◯ No

17. During this hospital stay, did you get information in writing about what symptoms or health problems to look out for after you left the hospital?
    - ◯ Yes
    - ◯ No

OVERALL RATING OF HOSPITAL

Please answer the following questions about your stay at the hospital named on the cover letter. Do not include any other hospital stays in your answers.

18. Using any number from 0 to 10, where 0 is the worst hospital possible and 10 is the best hospital possible, what number would you use to rate this hospital during your stay?
    - ◯ 0 Worst hospital possible
    - ◯ 1
    - ◯ 2
    - ◯ 3
    - ◯ 4
    - ◯ 5
    - ◯ 6
    - ◯ 7
    - ◯ 8
    - ◯ 9
    - ◯ 10 Best hospital possible

19. Would you recommend this hospital to your friends and family?
    - ○ Definitely no
    - ○ Probably no
    - ○ Probably yes
    - ○ Definitely yes

UNDERSTANDING YOUR CARE WHEN YOU LEFT THE HOSPITAL

20. During this hospital stay, staff took my preferences and those of my family or caregiver into account in deciding what my health care needs would be when I left.
    - ○ Strongly disagree
    - ○ Disagree
    - ○ Agree
    - ○ Strongly agree

21. When I left the hospital, I had a good understanding of the things I was responsible for in managing my health.
    - ○ Strongly disagree
    - ○ Disagree
    - ○ Agree
    - ○ Strongly agree

22. When I left the hospital, I clearly understood the purpose for taking each of my medications.
    - ○ Strongly disagree
    - ○ Disagree
    - ○ Agree
    - ○ Strongly agree
    - ○ I was not given any medication when I left the hospital

ABOUT YOU

23. During this hospital stay, were you admitted to this hospital through the Emergency Room?
    - ○ Yes
    - ○ No

24. In general, how would you rate your overall health?
    - ○ Excellent
    - ○ Very good
    - ○ Good
    - ○ Fair
    - ○ Poor

25. In general, how would you rate your overall mental or emotional health?
    - ○ Excellent
    - ○ Very good
    - ○ Good
    - ○ Fair
    - ○ Poor

continue to page 3

26. What is the highest grade or level of school that you have completed?
   - ○ 8th grade or less
   - ○ Some high school, but did not graduate
   - ○ High school graduate or GED
   - ○ Some college or 2-year degree
   - ○ 4-year college graduate
   - ○ More than 4-year college degree

27. Are you of Spanish, Hispanic or Latino origin or descent?
   - ○ No, not Spanish/Hispanic/Latino
   - ○ Yes, Puerto Rican
   - ○ Yes, Mexican, Mexican American, Chicano
   - ○ Yes, Cuban
   - ○ Yes, other Spanish/Hispanic/Latino

28. What is your race? Please choose one or more
   - ○ White
   - ○ Black or African American
   - ○ Asian
   - ○ Native Hawaiian or other Pacific Islander
   - ○ American Indian or Alaska Native

29. What language do you mainly speak at home?
   - ○ English
   - ○ Spanish
   - ○ Chinese
   - ○ Russian
   - ○ Vietnamese
   - ○ Portuguese
   - ○ German
   - ○ Some other language (please print):

INSTRUCTIONS: Mark the response that best describes your experience. If a question does not apply to you, please skip to the next question. Space is provided for you to comment on your experiences.

EMERGENCY DEPARTMENT	very poor 1	poor 2	fair 3	good 4	very good 5
1. Courtesy of Emergency Room staff	○	○	○	○	○
2. How well you were kept informed about your medical condition and treatment	○	○	○	○	○
3. Amount of time you had to wait in the Emergency Department/Room before you were admitted to your room	○	○	○	○	○

Comments (describe good or bad experience):

ROOM	very poor 1	poor 2	fair 3	good 4	very good 5
1. Courtesy of the person who cleaned your room	○	○	○	○	○
2. Room temperature	○	○	○	○	○

Comments (describe good or bad experience):

MEALS	very poor 1	poor 2	fair 3	good 4	very good 5
1. Temperature of the food (cold foods cold, hot foods hot)	○	○	○	○	○
2. Quality of the food	○	○	○	○	○
3. Courtesy of the person who served your food	○	○	○	○	○

Comments (describe good or bad experience):

NURSES	very poor 1	poor 2	fair 3	good 4	very good 5
1. Nurses' attitude toward your requests	○	○	○	○	○
2. Amount of attention paid to your special or personal needs	○	○	○	○	○
3. How well the nurses kept you informed	○	○	○	○	○

Comments (describe good or bad experience):______________________________

DOCTORS	very poor 1	poor 2	fair 3	good 4	very good 5
1. Time doctors spent with you	○	○	○	○	○
2. Doctors' concern for your questions and worries	○	○	○	○	○
3. How well doctors kept you informed	○	○	○	○	○

Comments (describe good or bad experience):______________________________

SPECIAL SERVICES	very poor 1	poor 2	fair 3	good 4	very good 5
1. Your rating of Physical and/or Occupational Therapy while in the hospital	○	○	○	○	○
2. Your rating of respiratory care	○	○	○	○	○
3. Explanation of test/treatment by Respiratory Therapist	○	○	○	○	○

Comments (describe good or bad experience):______________________________

DISCHARGE	very poor 1	poor 2	fair 3	good 4	very good 5
1. Extent to which you felt ready to be discharged	○	○	○	○	○
2. Speed of discharge process after you were told you could go home	○	○	○	○	○
3. Instructions given about how to care for yourself at home	○	○	○	○	○
4. Explanations regarding taking medicine after discharge (including potential side-effects)	○	○	○	○	○
5. How well the case manager assisted you with discharge planning	○	○	○	○	○

Comments (describe good or bad experience):______________________________

PERSONAL ISSUES	very poor 1	poor 2	fair 3	good 4	very good 5
1. Staff concern for your privacy	○	○	○	○	○
2. How well staff addressed your emotional needs	○	○	○	○	○
3. Response to concerns/complaints made during your stay	○	○	○	○	○
4. Staff effort to include you in decisions about your treatment	○	○	○	○	○

this section continued on page 5

PERSONAL ISSUES (...continued)	very poor 1	poor 2	fair 3	good 4	very good 5
5. How well the staff individualized their care to optimize my comfort	○	○	○	○	○

Comments (describe good or bad experience):______________________________

OVERALL ASSESSMENT	very poor 1	poor 2	fair 3	good 4	very good 5
1. How well staff worked together to care for you	○	○	○	○	○
2. Likelihood of your recommending this hospital to others	○	○	○	○	○
3. Overall rating of care given at hospital	○	○	○	○	○
4. Degree to which you were treated as a whole person whose physical, spiritual, and emotional needs were addressed	○	○	○	○	○

Comments (describe good or bad experience):______________________________

During your hospital stay, did a doctor and nurse visit you (round) together at least once a day?

○ Never ○ Usually ○ Always
○ Sometimes

Please provide contact information if the hospital needs to contact you. This information is not required.

Patient's Name: *(optional)*______________________________

Telephone Number: *(optional)*______________________________

THANK YOU
Please return the completed survey in the postage-paid envelope.

Appendix G: Logistic Regression Assumptions Testing for RQ 1

Table G1

Coefficients[a] Table (January 2017–April 2021)

Model	Collinearity Statistics Tolerance	VIF
Age	.763	1.310
Gender	.989	1.011
Insurance Coverage	.767	1.304
(Index) Initial Diagnosis	.977	1.033
Before/After BOOST Tool	.984	1.016

a. Dependent Variable: 30-Day Readmission

Table G2

Casewise List[b] for Outliers

Case (Patient ID)	Selected Status[a]	Observed 30-Day Readmission	Predicted	Predicted Group	Resid	ZResid	SResid
1278	S	1**	.133	0	.867	2.552	2.032
1260	S	1**	.136	0	.864	2.517	2.026
1265	S	1**	.125	0	.875	2.647	2.069
1266	S	1**	.122	0	.878	2.679	2.076
1282	S	1**	.116	0	.884	2.756	2.109
1285	S	1**	.110	0	.890	2.846	2.135
1296	S	1**	.124	0	.876	2.659	2.081
1302	S	1**	.118	0	.882	2.729	2.108
1295	S	1**	.097	0	.903	3.046	2.199
1301	S	1**	.099	0	.901	3.010	2.195
1295	S	1**	.069	0	.931	3.685	2.360
1300	S	1**	.072	0	.928	3.577	2.341
1299	S	1**	.040	0	.960	4.894	2.593
1284	S	1**	.089	0	.911	3.199	2.237

a. S=Selected, U=Unselected cases, and **=Misclassified cases

b. Cases with studentized residuals greater than 2.000 are listed

Appendix H: Linear Regression Assumptions Testing for RQ 2

Figure H1

Normal P-P Plot of Regression Standardized Residual for Length of Stay

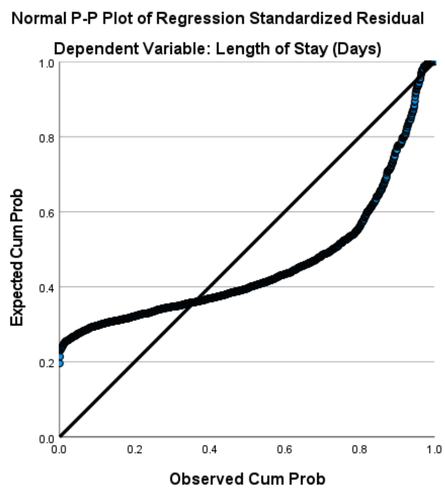


Figure H2

Normal P-P Plot of Log 10 for Length of Stay

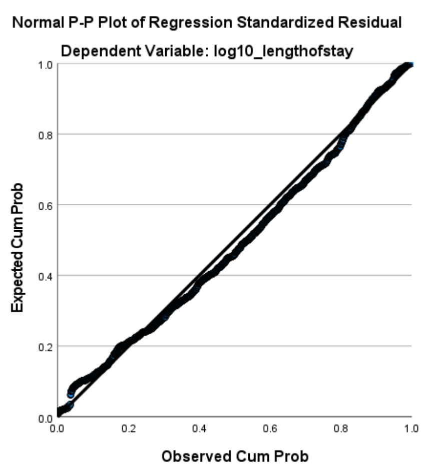


Figure H3

Histogram of Length of Stay

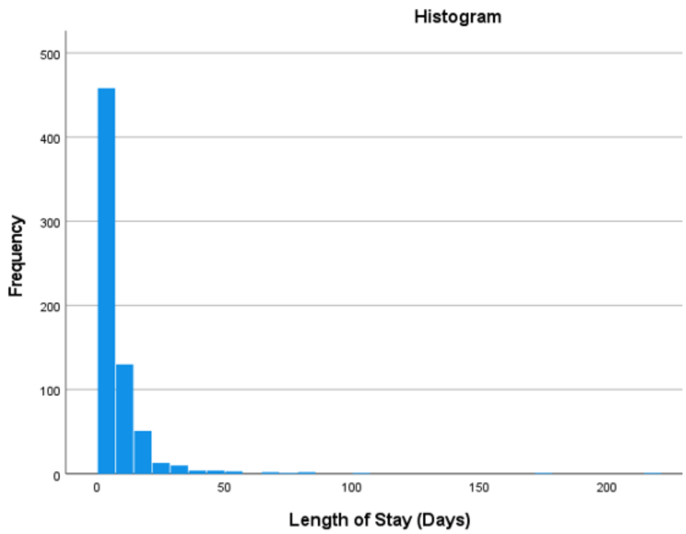


Figure H4

Log 10 Length of Stay Histogram

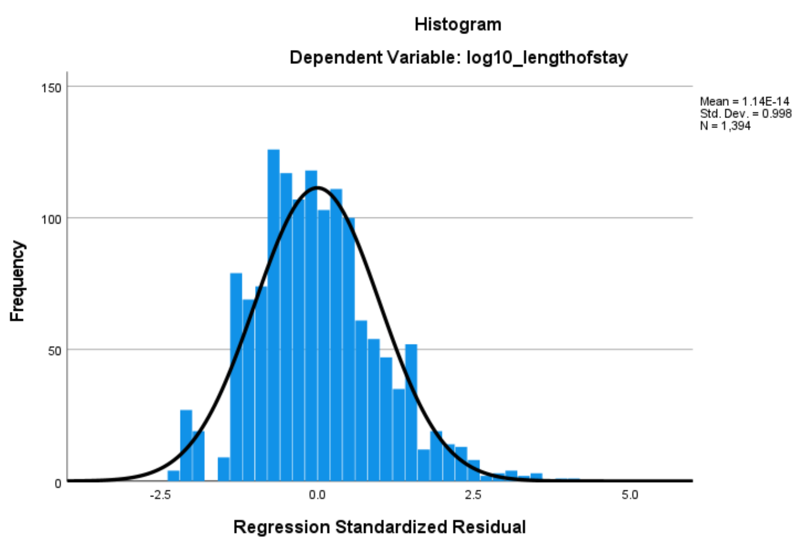


Figure H5

Scatterplot for Length of Stay

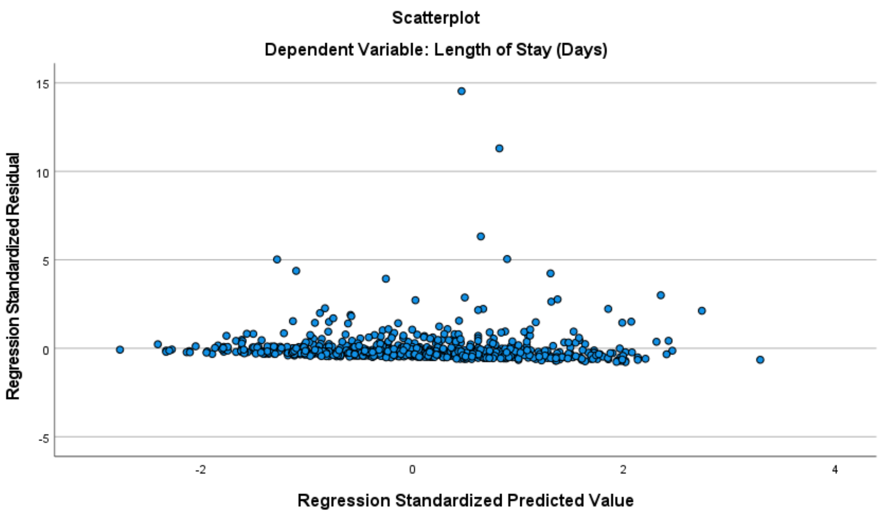


Figure H6

Scatterplot for Log10 Length of Stay

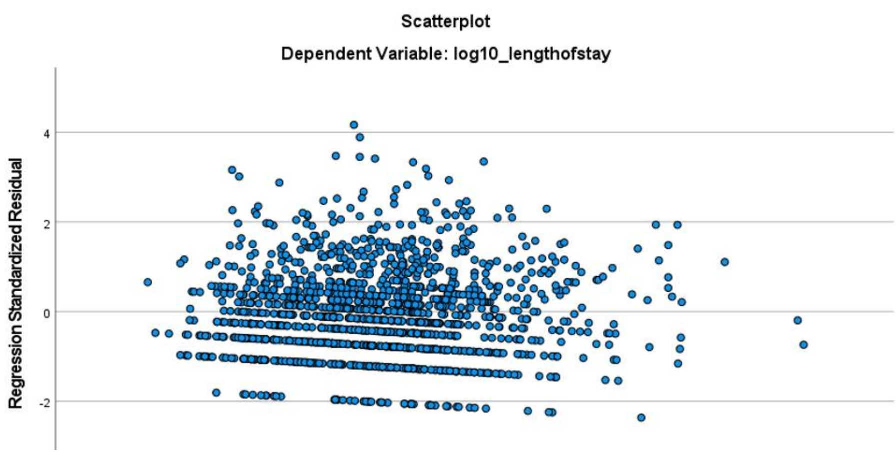


Table H1

Descriptives for Log 10 Length of Stay

			Statistic	Std. Error
Log10_Length of Stay (Days)	Mean		.7689	.01025
95% Confidence Interval for Mean		Lower Bound	.7488	
		Upper Bound	.7890	
5% Trimmed Mean			.7563	
Median			.6990	
Variance			.146	
Std. Deviation			.38265	
Minimum			.00	
Maximum			2.34	
Range			2.35	
Interquartile Range			.52	
Skewness			.538	.066
Kurtosis			.510	.131