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Impact of Queueing Theory on Capacity Management in the Emergency Department

Nina Bush
Walden University

Walden University

College of Health Sciences

This is to certify that the doctoral study by

Nina Bush

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Review Committee
Dr. Matt Frederiksen-England, Committee Chairperson, Health Sciences Faculty
Dr. Rabeh Hijazi, Committee Member, Health Sciences Faculty
Dr. Miriam Ross, University Reviewer, Health Sciences Faculty

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2019

Abstract

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MA, Bradley University, 2013

BS, Bradley University, 2009

Doctoral Study Submitted in Partial Fulfillment

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Abstract

Hospital systems in the United States are facing a dilemma regarding capacity management in the emergency department (ED) and the inpatient care setting. The average wait time in EDs across the United States exceeds 98 minutes, which is also the point at which patients begin to abandon healthcare treatment. The purpose of this quantitative study was to examine the use of queueing theory in capacity management on length-of-stay (LOS) rates, left-without-being-seen (LWBS) rates, and boarding rates in the ED and inpatient setting. The boarding rates represent the rate in which patients were roomed in the ED but required inpatient care. This study assessed the relationships between capacity management using queueing theory and a reduction in the aforementioned rates compared to traditional processes across systems within the continental United States. A linear regression analysis with a confidence interval 95% paired with an independent sample *t* test was used to analyze the secondary datasets. A sample size of approximately 33,000 patients was tested in the areas of LOS, LWBS, and boarding. The results of the analysis determined that access was improved in the ED and inpatient setting when queueing theory was deployed within the hospital system compared to traditional processes for managing capacity within the system. Queuing theory used for capacity management resulted in lower LOS, LWBS, and boarding rates. The implications of this study for positive social change include the opportunity to provide greater access to care for the population as a whole, and better health outcomes for the promotion of population health.

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Dedication

This study is dedicated to the healthcare systems that choose innovation and change for the betterment of patient care and the individuals within those systems who push change and demand the impossible. This study is also for the patients who demand quality and affordable care as well as the right to fluid access to that care. I also dedicate this study to my mother for pushing me to always be my best and being the rock to our entire family, including never letting her children take the easy way out. You are an inspiration, role model, and you mean more to me than words can ever describe. To my family for understanding the long hours and being supportive, even when going to the park would be more fun. To Michael for pushing the boundaries of healthcare and being a fighter. Never stop fighting and never stop demanding the right care.

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Section 1: Foundation of the Study and Literature Review

Emergency department (ED) abandonment or left without being seen (LWBS) rates are having detrimental effects on the ability for systems to service patients due to extended wait times, length of stay (LOS), within the ED and poor capacity management (Pasupathy et al., 2017). Researchers have shown that the mean wait time for abandonment is 98 minutes, and many EDs are exceeding the 98-minute mark for patients who do not need care rendered within 1 to 14 minutes (Pasupathy et al., 2017). Hospital systems in the United States are facing a research dilemma regarding capacity management within the ED and the inpatient care setting (Storm-Versloot et al., 2014).

Queueing theory looks at the different paths that an object travels throughout a system and may be helpful to regulate capacity management barriers based on statistics and differential equations that see patients as moving parts through a systematic and mechanic means (Armony et al., 2015). Capacity management barriers contribute to LOS, hospital systems seeing a higher rate of LWBS, and a reduction in clinical outcomes and higher mortality (Armony et al., 2015). Patients who are needing to be seen within 1 to 14 minutes are not being seen for 37 minutes, while lower acuity patients are being seen in times that surpass the 37-minute mark for triaging purposes prior to rooming ("Emergency Department Wait Times, Crowding and Access," 2014). Patients who encounter long wait times, or perceive a long wait to obtain care, are more likely to rate clinical care as poor in patient satisfaction surveys, regardless of the actual standard of clinical care provided (Storm-Versloot et al., 2014).

Rooming is the act of moving the patient from the ED wait room or triage room to a designated ED room. Capacity management impacts the system as a whole, but the extent that the system is impacted has not been heavily researched and represents a need within the health care field. ED overcrowding due to patient boarding, the act of keeping patients within the ED when emergent care is not required, decreases patient quality and patient satisfaction (Chang et al., 2017). Patient boarding reduces the number of beds available to render care to patients. The reduction is a result of the inpatient setting using ED beds for inpatient patients (Chang et al., 2017). There is a national crisis in the United States with overcrowding within the ED and inpatient setting. The overcrowding is caused by patients improperly using the ED for acute health care needs, paired with patients being moved to the inpatient care setting due to improper acuity and triage evaluations within the ED that would not warrant inpatient care, which has led to a higher mortality rate and lower patient satisfaction within hospital systems (Chang et al., 2017). The inclusion of new knowledge regarding the impact of capacity management using queueing theory can allow health systems to implement solutions for capacity management barriers, which can ensure better clinical outcomes and patient engagement with the health system.

In Section 1, I introduce the study topic and provide background information on the use of queuing theory to regulate capacity management within the ED and inpatient setting and the impact of the use of queueing theory in capacity management in reducing LOS, LWBS, and boarding rates. After presenting the problem statement, purpose, and research questions, I briefly summarize the use of queueing theory and how this theory applies to capacity management within the ED and inpatient setting. I continue with the nature of the study, definitions, and a discussion of the study's assumptions, limitations, scope, and delimitations. I conclude the section with a discussion of the study's significance and a section summary.

Background

Ljungbeck and Sjögren Forss (2017) stated that an increase in the population requiring health care services creates a burden on healthcare systems, as individuals are requiring health care later in life due to an increasing aging population. The expansion of healthcare professionals, such as advanced nurse practitioners, help offset the burden by expanding the continuum of care for patients and access through staffing models (Ljungbeck & Sjögren Forss, 2017). However, if capacity is limited, staff can only be effective to the capacity barrier or position in which there is no more room to see patients. EDs are often the first point of contact for patients entering the hospital system. ED abandonment or LWBS rates are having detrimental effects on the ability for systems to service patients due to extended wait times, LOS within the ED, and poor capacity management that results in patients being boarded within the ED setting where the level of care required is not appropriate for the emergent care setting (Pasupathy et al., 2017).

Capacity Management

Clinical processes and work flow within the ED care setting cannot be compared to any other clinical or health care setting due to the complex and unpredictable nature of the levels of care as well as the clinical decision-making process often being more complex (Georgiou et al., 2013). Health technology services, the use of electronic medical records and digital workflows, were observed to help standardize provider order entry systems. Implementing design reprocessing within the ED setting can help contribute to a reduction of LOS, which allows for the capacity to be better managed within the ED through effective patient flow management through the EMR. The purpose of capacity management is to assist the patient through the health system through the management of patient flow.

Queueing Theory

Queueing theory looks at the different paths that an object travels throughout a system and may be helpful to regulate capacity management barriers based on statistics and differential equations that see patients as moving parts through a systematic and mechanic means (Armony et al., 2015). As previously stated, capacity management barriers contribute to longer LOS, hospital systems seeing a higher rate of LWBS, and a reduction in clinical outcomes and higher mortality (Armony et al., 2015). Queuing theory uses a Poisson process, the probability of an event occurring, and suggests that queue lines or processes of throughput have fluid limits and can be predicted through the use of mathematical equations (Heyde, 2001). Routing algorithms can determine the optimal throughput of a patient by depicting the nodes of services in which the patient may travel and assist in the patient flow process.

Emergency Department Length of Stay, Left Without Being Seen, and Boarding

Capacity management barriers contribute to longer LOS rates for patients within the ED setting due to patients encountering systematic barriers within the patient journey through the system (Armony et al., 2015). The result of encountering systematic barriers contributes to patients not obtaining medical care in a timely fashion, which correlates to a longer LOS (Chang et al., 2017). Long wait times prior to being placed into a room within the ED and inpatient setting, including longer than expected LOS, is related to lower patient satisfaction with the perceived quality of care in which the patient receives and higher LWBS rates (Storm-Versloot et al., 2014). Researchers have shown that the mean wait time for abandonment is 98 minutes, and many EDs are exceeding the 98-minute mark for patients who do not need care rendered within 1 to 14 minutes, with many patients leaving without being seen (Pasupathy et al., 2017). Hospital systems in the United States are facing a research dilemma regarding capacity management within the ED and the inpatient care setting due to limited research in the field of capacity management within a nonmanufacturing setting (Storm-Versloot, 2014).

Chang et al. (2017) provided insight into the impact of ED overcrowding and patient boarding from the inpatient setting on decreased patient quality and patient satisfaction. Patient boarding within the ED setting, due to overcrowding in the inpatient setting, impacted the ED setting by reducing the number of beds available to render care to patients. The national crisis in the United States with overcrowding by patients improperly using the ED for health care needs, paired with patients being moved to the inpatient care setting due to improper acuity and triage evaluations, has led to a higher mortality rate and patient satisfaction within hospital systems, as well as higher boarding rates within the ED (Chang et al., 2017). Hospital systems with a high-performance classification, standardization of processes and tools across the system, employed a magnitude of strategies in order to reduce boarding rates, including executive leadership involvement, cross-hospital coordination, data and metric driven reporting, and performance accountability (Change et al., 2017). The results are consistent to research in the health care field that relayed the importance of administrative involvement across the continuum of care and the need for standardization of capacity management processes across the hospital system as a whole and not solely on a departmental level.

Problem Statement

ED abandonment or LWBS rates are having detrimental effects on the ability for systems to service patients due to extended wait times, LOS within the ED, and poor capacity management (Pasupathy et al., 2017). Hospital systems in the United States are facing a research dilemma regarding capacity management within the ED and the inpatient care setting (Storm-Versloot et al., 2014).

Queueing theory looks at the different paths that an object travels throughout a system and may be helpful to regulate capacity management barriers based on statistics and differential equations that see patients as moving parts through a systematic and mechanic means (Armony et al., 2015). Capacity management barriers contribute to longer LOS rates for patients, hospital systems seeing a higher rate of LWBS, and a reduction in clinical outcomes and higher mortality (Armony et al., 2015).

Patient satisfaction is also impacted, as patients may determine quality of care subpar if wait times exceed the patient's desired wait, regardless of the actual quality of care provided to the patient, which directly impacts a system's ability to be reimbursed for services (Storm-Versloot et al., 2014). Patients who are needing to be seen within 1 to 14 minutes are not being seen for 37 minutes, while lower acuity patients are being seen in times that surpass the 37-minute mark for triaging purposes prior to rooming ("Emergency Department Wait Times, Crowding and Access," 2014). Rooming is the act of moving the patient from the ED wait room or triage room to a designated ED room. Capacity management impacts the system as a whole, but the extent that the system is impacted has not been heavily researched and represents a need within the health care field.

Clinical processes and work flow within the ED care setting cannot be compared to any other clinical or health care setting. One reason for the inability to standardize capacity management and clinical processes across a health system is due to the complex and unpredictable nature of the levels of care, including the clinical decision-making process often being more complex (Georgiou et al., 2013). Patients who encounter long wait times, or perceive a long wait to obtain care, are more likely to rate clinical care as poor in patient satisfaction surveys, regardless of the actual standard of clinical care provided (Storm-Versloot et al., 2014). ED overcrowding due to patient boarding, the act of keeping patients within the ED when emergent care is not required, decreases patient quality and patient satisfaction (Chang et al., 2017). Patient boarding reduces the number of beds available to render care to patients. The reduction is a result of the inpatient setting using ED beds for inpatient patients (Chang et al., 2017). There is a national crisis in the United States with overcrowding within the ED and inpatient setting. The overcrowding is caused by patients improperly using the ED for acute health care needs, paired with patients being moved to the inpatient care setting due to improper acuity and triage evaluations within the ED that would not warrant inpatient care, which has led to a higher mortality rate and lower patient satisfaction within hospital systems (Chang et al., 2017). The inclusion of new knowledge regarding the impact of capacity management using queueing theory will allow health systems to implement solutions for capacity management barriers, which will ensure better clinical outcomes and patient engagement with the health system.

Purpose of the Study

The purpose of this study was to examine the use of queueing theory in capacity management and the impact of queueing theory when used within capacity management on LOS, LWBS rates, and boarding rates within the ED and inpatient setting. I assessed if there was a relationship between capacity management, the process of moving patients throughout the system, and a reduction in the LWBS rate and inpatient boarding (see Armony et al., 2015). There is a correlation between patient satisfaction and the LWBS rate due to extended wait times within the ED (Pasupathy et al., 2017), as well as poorer clinical outcomes for the patient (Storm-Versloot et al., 2014). Patient satisfaction and clinical outcomes directly impact a hospital system's ability to be reimbursed for services (Thiels et al., 2016).

In this study, I looked at the hospital system as a manufacturing system of moving parts, much like a manufacturing plant, which is where queueing theory is rooted. The patient represents the parts moving through the system with the completion of the process at patient discharge from the system. Barriers within the process, such as in departments like the ED or inpatient setting, can cause systematic disruption with the patient's journey through the system (Chang et al., 2017). The systematic disruption has a trickle-down effect on clinical outcomes and hospital reimbursement, and the impact of capacity management within the ED and inpatient setting on system outcomes is not widely reviewed and analyzed (Chang et al., 2017). The gap is further supported by Georgiou et al. (2013) who emphasized that solutions to reduce capacity management barriers are limited within research and need further attention in order to be mitigated, which according to Change et al. (2017), is still an ongoing issue.

Research Questions and Hypotheses

Research Question (RQ) 1: Is there a relationship between capacity management utilizing Queueing theory and Length of Stay (LOS) in the emergency department (ED)?

H_1: There is a statistically significant difference between capacity management using queuing theory to reduce LOS in the ED.

H_{01}: There is not a statistically significant differences between capacity management using queuing theory to reduce LOS in the ED.

RQ2: Is there a reduction in the abandonment rate or LWBS rate when capacity management is used within the ED setting?

H_2: There is a statistically significant difference between capacity management using queuing theory to reduce LWBS in the ED.

H_{02}: There is not statistically significant difference between capacity management using queuing theory to reduce LWBS in the ED.

RQ3: Is there a relationship between capacity management within the ED and inpatient setting and inpatient boarding rates within the ED?

H_3: There is a statistically significant difference between capacity management using queuing theory to reduce in-patient boarding rates in the ED.

H_{03}: There is not a statistically significant difference between capacity management using queuing theory to reduce in-patient boarding rates in the ED.

The independent variable used for this study was capacity management pertaining to the number of patients who enter the ED or inpatient setting. The dependent variables were LOS, LWBS or abandonment rate, and boarding rate within the ED. LOS, LWBS rate, and boarding rate were compared by analyzing the LOS, LWBS rate, and boarding rate of systems that use queueing theory for capacity management and systems that do not use queuing theory for capacity management.

Theoretical Framework

The theoretical framework for this study was Erlang's (1909) queueing theory. Queuing theory uses a Poisson process that suggests that queue lines or processes of throughput have fluid limits and can be predicted through the use of mathematical equations (Heyde, 2001). Routing algorithms can determine the optimal throughput of a patient by depicting the nodes of services in which the patient may travel. Erlang's use of queueing theory provides a mathematical approach to modeling possible pathways a patient may take within a health system as well as barriers that may arise to disrupt a service node or a patient's throughput. Subsequent research and application using Erlang's queuing theory offers support of the use of queueing theory in the hospital system setting in order to improve organizational performance and the increase in health care and patient demand (Bittencourt, Verter, & Yalovsky, 2018).

The variable that cannot be controlled or predicted in advance in a health system is representative of the population who enters the health system. The pathways are also random, as a patient's modality and service needs have many influencers that are random dependent on the individual patient. The health system has control of the efficiency of the pathways that a patient may travel through, and the use of queueing theory allows for the barriers to efficiency to be noted and adapted. In a health system, inefficient practices lead to higher LOS, LWBS rates, and boarding rates (Chang et al., 2017). Queueing theory is used to depict the barriers within pathways to allow for fluidity into service nodes. The effects of the use of queueing theory in the reduction of barriers within the pathways was the framework of the study, where I specifically examined the outputs of LOS, LWBS rate, and boarding rates within the ED and inpatient setting.

Nature of the Study

The nature of this study was quantitative and measured the use of capacity management using queueing theory in the ED and in-patient setting compared with the outcome measures of LOS, LWBS rates, and abandonment rates. LOS, LWBS rates, and abandonment rates were reviewed from systems that have implemented queueing theory approaches within capacity management protocols compared to systems that use traditional capacity management without queueing theory simulation across time. This quantitative analysis helped define the benefit of the use of queueing theory within capacity management in a hospital system, specifically in the ED and inpatient setting.

Definitions

Capacity management: Forecasting demand and planning capacity for health services rendered to a patient population and system flow (Sharifi & Saberi, 2014).

Emergency department boarding: The practice of holding patients in the emergency department after they have been admitted to the hospital, because no inpatient beds are available ("Definition of Boarded Patient", 2018).

Emergency department left without being seen: A patient who has left a healthcare facility without examination or treatment post check-in (Segan, 2006).

Emergency department length of stay: The time of arrival in the emergency department to time of discharge as documented in the electronic medical records or manual system (Parker & Marco, 2014).

Emergency severity index acuity: A five-level emergency department triage algorithm that provides clinically relevant stratification of patients into five groups from 1 (*most urgent*) to 5 (*least urgent*) on the basis of acuity and resource needs ("Emergency Severity Index [ESI)]", 2019).

Queueing theory: The study of queues and the random processes that characterize them making mathematical sense of real-life scenarios ("Queueing Theory and Modeling", 2017).

Assumptions

Several assumptions informed this study. I assumed that all hospital systems employ some type of capacity management processes or system. Differences in capacity management processes or systems may influence varying results in LOS, LWBS, and boarding rates. Another assumption was that the data entered into the EMRs and submitted to the national surveys were accurate. Finally, I assumed that there was no pattern to any missing information. Overt inaccuracies and a pattern of missing data could bias the study results.

Scope and Delimitations

The scope of this study was dictated by the source of the archival data: data collection within the date range of January 1, 2008 and December 31, 2008 from hospital system EDs that participated in the NEDS and NHAMC surveys and hospital systems from a primary study using queueing theory for capacity management that was excluded from national surveys. For this study, the archival data consisted of deidentified data from adults 18 years of age or older who entered the participating system's EDs, had an ESI acuity of a 3 or higher, and were not hospitalized for more than 4 days. This study was delimited to the examination of the relationship between health systems that use queueing theory for capacity management and systems that do not use queueing theory for capacity management in the ED; I did not consider any association with direct admits or protocols of diversion post system activation of a diversion protocol. I measured the relationship between the systems using queueing theory for capacity management and systems that do not use queueing theory for capacity management by analyzing LOS, LWBS, and boarding rates. The results of this study are intended to be generalizable to adults 18 years and older who engage a hospital's emergency department for medical care.

Limitations

The most important limitation in this study was the use of archival data from a previous study of the use of queueing theory in a health system (see Wiler, Bolandifar, Griffey, Poirier, & Olsen, 2013), as well as the NEDS and NHAMC national surveys. Selection, quality, included variables, and the method of data collection were not under my control, and validation was not be possible. An additional limitation was that the data for the national surveys were subject to the data collected and dispersed by the individual health systems. A third limitation was the inability to determine the standardization of data collection processes due to varying EMR systems within the health systems where data were collected. While the final limitation was the mix of urban and rural system data, the queueing theory data did not include rural systems.

Significance

An increase in the population requiring health care services creates a burden on healthcare systems, as individuals are requiring health care later in life due to an increasing aging population (Ljungbeck & Sjögren Forss, 2017). The expansion of healthcare professionals, such as advanced nurse practitioners, help offset the burden by expanding the continuum of care for patients and access through staffing models (Ljungbeck & Sjögren Forss, 2017). However, if capacity is limited, staff can only be effective to the capacity barrier, or position in which there is no more room to see patients. Storm-Versloot et al. (2014) emphasized the barriers capacity has on the ED and inpatient setting, and that the problem is growing exponentially due to the U.S. population having a greater need for health care services. The barriers regarding capacity management within the ED lead to higher wait times for patients, longer LOS, and a higher rate of LWBS (Chang et al, 2017).

In this study, I acknowledged the greater need for health care services but aimed to address the barriers within the system and the effectiveness and efficiency of systems to move patients through the health care service process, regardless of the patient population being served. Capacity management should adapt to fit the needs of a health system independent of the population base that requires care, as systems cannot predict with certainty the acuity or needs of the population prior to the patient entering the system. Queuing theory addresses the unknown factors of the patient's health care needs by simulating all possible care paths within the system by depicting internal system barriers within the possible paths as well as the paths of least resistance. If capacity management is effectively designed, then health care systems would be able to better adapt to fit the needs of the growing health care population and improve the access to health care for the population. The improved access across the system should also directly influence capacity within the ED, with the goal of reducing wait times, LOS, and decreasing the LWBS rate.

Summary

EDs are seeing an increase in the number of patients entering the ED with the intent to have care rendered, which is having a detrimental effect on the system's ability to manage capacity and the ability of the system to render medical care to patients due to extended wait times within the ED (Pasupathy et al., 2017). Capacity management barriers, in return, contribute to longer length of LOS rates, hospital systems seeing a higher rate of LWBS, and a reduction in clinical outcomes and higher mortality (Armony et al., 2015). Additionally, poor capacity management leads to higher patient boarding within the ED that reduces the number of beds available to render care to patients. The reduction is a result of the inpatient setting using ED beds for inpatient patients (Chang et al., 2017). Ineffective capacity management could contribute to a hospital system being unable to adequately, efficiently, or effectively render care to the population that the system serves, specifically emergent care needs.

Queueing theory assesses the nodes and pathways that a patient may encounter when having care rendered. Capacity management using queueing theory may assist in assessing and determining systematic barriers that could be resulting in a longer LOS, higher LWBS rates, and higher boarding rates. Queueing theory has been successfully implemented in the manufacturing setting, and by design could be beneficial in managing capacity within a hospital system due to similar systematic components. Patient flow through a hospital system is similar to deliverables moving through a manufacturing system. By implementing an effective capacity management system, such as queueing theory, hospital systems could provide more effective and efficient care to the patients the system serves, while reducing LOS, LWBS rates, and boarding rates.

This section contained an overview of the research objectives, theories, and details of the specific research questions for this study. My aim in this study was to evaluate the relationship between systems that use queueing theory for capacity management and systems that do not use queueing theory for capacity management in regards to LOS, LWBS rates, and boarding rate. Descriptions of the nature and purpose of the study, study design, scope, limitations, and significance of the study were provided.

Literature Review

Introduction

Hospital systems in the United States are facing a research dilemma regarding capacity management within the emergent care setting of the ED as well as the inpatient care setting. The capacity management barriers have been shown to contribute to patients having a LOS, hospital systems seeing a higher rate of LWBS, and a decrease in patient satisfaction (Chang et al., 2017). There is a gap in understanding in terms of the components that may negatively impact capacity management (Pasupathy et al., 2017). There is a lack of knowledge regarding possible implementation solutions within the ED and inpatient setting that could aid in a reduction of LOS, LWBS, as well as a reduction in boarding rates (Chang et al., 2017). Through the implementation of possible solutions, a hospital system can begin to have a better understanding of how to manage capacity management within the emergent care and inpatient setting as well as provide better access to care for patients.

In this study, I selected peer-reviewed articles relating to queueing theory and capacity management within ED and inpatient setting as well as factors that may cause capacity management barriers. The keywords searched were *capacity management, queueing theory, ED wait times, inpatient boarding, ED abandonment, clinical excellence ED,* and *patient flow within systems* in the databases BioMed Central, Annals of Emergency Medicine, and Emergency Medicine Journals, as well as PubsOnline, Google Scholar, and Walden University journal database. The years of research used occurred within the last 5 to 7 years.

Use of Technology for Capacity Management

Clinical processes and workflow within the ED care setting cannot be compared to any other clinical or health care setting due to the complex and unpredictable nature of the levels of care as well as the clinical decision-making process often being more complex (Georgiou et al., 2013). Health technology services, the use of EMRs and digital workflows, were observed to help standardize provider order entry systems. Georgiou et al. (2013) reviewed hospital systems that used EMRs to manage capacity management and patient flow, specifically EMR tracking software for the purpose of capacity management. Twenty-two health systems, 20 in the United States, one in France, and one in Korea, participated in the study. The 22-health system's EMR entries were assessed in the key outcome areas of patient flow/clinical work, decision support systems, and safety (Georgiou et al., 2013). Quantitative data collection was used reviewing the key outcome areas and the response time for the data entered within the health system's EMR (Georgiou et al., 2013). The purpose of the study was to create a mechanism for efficient workflow and data entry processes to reduce the minutes a clinician spends on nonpatient-oriented tasks, thus reducing LOS (Georgiou et al., 2013).

Georgiou et al. (2013) explained that the implementation of the key outcomes of patient flow/clinical work, decision support systems, and safety management within a hospital system's EMR contributed to a level of efficiency with the clinicians that directly impacted a patient's LOS with an average reduction of 1.94 hours. The authors further elaborated that implementing process systems should not be duplicated across other care settings due to the ED presenting as a unique environment (Georgiou et al., 2013). However, implementing design reprocessing within the ED setting can help contribute to a reduction of LOS, which allows for capacity to be better managed within the ED through effective patient flow management through the EMR. Georgiou et al. (2013) acknowledged that further research is needed regarding the benefits of health technology management and the use of a system's EMR to address process barriers. The study was limited in nature to 22 health systems, which was a relatively low sample size for the complexity and differences EDs may have across many health systems. There is an opportunity to expand research regarding the use of health technology for the purpose of capacity management.

The use of health technology for capacity process management is useful in the health care field, as seen by Georgiou et al.'s (2013) explanation of using provider order entries and clinical work flows/patient flows for creating efficiencies within the ED setting. As more hospital systems adapt EMR applications, research regarding maximizing the use of the applications for capacity management could potentially have a significant impact on ensuring patient access within the emergent care setting and inpatient care setting. However, more information and research are needed due to the complexities of health care systems and the different classifications represented within health care systems, including the rural and urban classification.

Impact of Length of Stay Rates

Long wait times prior to being placed into a room within the ED and inpatient setting, including longer than expected LOS, is related to lower patient satisfaction with the perceived quality of care in which the patient receives (Storm-Versloot et al., 2014). Patient triage systems allow a health system and the health system's clinicians to prioritize patients according to the patient's needs. Although the acuity of the patient is reviewed, 1 being a trauma and a 5 being acute, there are not consistent rules across hospital systems how to classify patients within those categories. Storm-Versloot et al. (2014) emphasized the rationale behind the use of the Manchester Triage System (MTS) within the ED setting for the management of distribution times and levels of urgency. A hospital system cannot turn away patients once the patient has arrived within the ED care setting due to the Emergency Medical Treatment and Labor Act (EMTALA), and Storm-Versloot et al. emphasized within the study that patients are actively bypassing primary care providers to obtain care within the ED. EMTALA came into effect in 1986 and was a part of the Consolidated Omnibus Budget Reconciliation Act, which emphasized patient rights in the areas of stabilization within the ED and employer mandated insurance postemployment ("Emergency Medical Treatment & Labor Act (EMTALA) - Centers for Medicare & Medicaid Services", 2019).

Storm-Versloot et al. (2014) explained that the MTS criteria and guidelines use didactic and practical training as well as national standards, allowing patients to be triaged effectively and only once, compared to duel triage systems completed by an ED Nurse. Storm-Versloot et al. outlined the study's progress through the implementation of the MTS protocol and the measurement of LOS, wait times, and patient satisfaction after the MTS protocol was used. Quantitative analysis using SPSS V.14.0 and a correlation factor of .05 were used for data collection purposes to review LOS, wait time, and patient satisfaction surveys to measure the success of the MTS protocol pre- and post-implementation via surveys and EMR data collection (Storm-Versloot et al., 2014).

MTS follows research that patient satisfaction results are directly linked to LOS and wait times within the ED. The implementation of MTS and the protocols examined by Storm-Versloot et al. (2014) removes duplicated processes and ensures that triage protocol is consistent across the patient spectrum. Storm-Versloot et al.'s study is relevant in terms of overcrowding in the ED and inpatient setting being an issue that has encompassed health systems across the United States, and the reduction of LOS, LWBS, and increase of patient satisfaction contributing to better quality of care metrics. Storm-Versloot et al. addressed limitations regarding the validity of patient satisfaction responses being questionable due to the limited response and participation that has been seen with patients actively engaging in patient satisfaction surveys. However, LOS and waiting room wait time data can be effectively gathered in large sample sizes through the use of EMR technology.

Storm-Versloot et al.'s (2014) explanation of the implementation of the MTS protocol is useful for hospital systems and hospital system administrators who are looking at implementation solutions for the management of capacity in the ED and inpatient setting. MTS is also useful for helping ED clinicians and leadership assess patients more effectively and consistently because of the inability to control the influx of patients who enter the ED, due to regulations such as EMTALA. However, MTS is one possible implementation protocol available for triage management. Further research and MTS's ability to adapt to health care reform and national standard changes needs to be assessed further. The implication on capacity management must also be reviewed more in-depth in terms of a long-term solution, as capacity management within the ED and inpatient setting is impacted by many other variables and possible causes, like inpatient boarding.

ED abandonment or LWBS rates are having detrimental effects on the ability for systems to service patients due to extended wait times, LOS within the ED, and poor capacity management (Pasupathy et al., 2017). Researchers have shown that the mean wait time for abandonment is 98 minutes, and many EDs are exceeding the 98-minute mark for patients who do not need care rendered within 1 to 14 minutes (Pasupathy et al., 2017). Hospital systems in the United States are facing a research dilemma regarding capacity management within the ED and the inpatient care setting due to limited research in the field of capacity management within a nonmanufacturing setting (Storm-Versloot, 2014).

Patient Boarding Within the ED

Chang et al.'s (2017) study provided insight into the impact of ED overcrowding and patient boarding from the inpatient setting on decreased patient quality and patient satisfaction. Patient boarding within the ED setting, due to overcrowding in the inpatient setting, has impacted the ED setting by reducing the number of beds available to render care to patients. The national crisis in the United States with overcrowding by patients improperly using the ED for health care needs, paired with patients being moved to the inpatient care setting due to improper acuity and triage evaluations, has led to a higher mortality rate and patient satisfaction within hospital systems (Chang et al., 2017). Chang et al. outlined the progress of the study to reduce mortality rates and overcrowding by developing strategies for hospital systems to use through the review of high-performing, low-performing, and high-performance hospital systems whose goal was to see a reduction in ED overcrowding. The performance metrics were set for each system by national standards for LOS and boarding. Additionally, Chang et al. used mixed-methods research within the case study to review the performance metrics of eight health systems compared to ED length of stay and boarding within each of the health systems.

Change et al. (2017) was consistent with other research in the field that suggests that health systems must employ a variety of strategies within the ED to manage capacity, strategies dependent on urban or rural hospital classifications. This study is relevant due to the importance quality of care and patient satisfaction has on hospital reimbursements, specifically if the hospital system is considered an Accountable Care Organization, as well as the emphasis on ensuring access to care for all patient populations within the US. Quantitative methods were employed by the authors to identify hospitals within the three defined performance metrics, and the raw result gathered from the hospital's ED timeliness metrics, as reported to Medicaid and Medicare Services. The results showed that hospital systems with a high-performance classification employed a magnitude of strategies in order to reduce LOS and boarding rates, including executive leadership involvement, cross-hospital coordination, data and metric driven reporting, and performance accountability (Change et al., 2017). The results were consistent to research in the health care field that relayed the importance of administrative involvement across the continuum of care. Furthermore, blind cold calling was utilized with current employees of the hospital system, who were not aware of performance rankings. The authors concluded that the interviewees had a shared theoretical model and perception of ED crowing and inpatient boarding (Chang et al, 2017). Overall the consensus was that services within the ED are not owned by the health system, due to there being a lack of control on the patients who receive care and a level of unpredictability. However, the authors did depict that the research was limited due to national benchmarking being delayed by a year or more, which means a health system could have employed unknown techniques prior to the public release of results, as well as qualitative hindrances regarding interviewees having a bias or perception regarding the hospital's performance bringing into question the effect of clinical and employee biases and perception on employed strategies.

Chang et al.'s (2017) study is relevant due to combining theories that there are process constraints within capacity management, as well as theoretical perceptions amongst a hospital system's staff that may contribute to an altered behavior by the staff in terms of strategy development. This piece is also relevant and useful for hospital administrators and the conversation revolving around linking benchmark metrics, such as boarding rates and LOS, to the human component and perceptions of the staff that render the services to the patient. Employing strategies that will be promoted by the staff, as well as having a shared understanding of the employed strategy will help a system be effective in implementation of the purposed strategy. The study also revealed that strategies are dependent on the nature of the hospital system, rural or urban, and that within the study no strategy was duplicated amongst the health systems reviewed. The lack of measurable consistency with the strategies utilized by health systems studied provided a significant limitation and promoted the need for further research in measurable and effective strategies to manage capacity management. More information is needed to determine the relationship between employee perceptions and CMS metrics in order to better define appropriate strategies within the ED and inpatient setting.

External Factors of Emergency Department and Inpatient Admission Rates

In O'Cathain et al. (2014), provide an insight into emergency admission rates and the influence urgent care and primary care settings have on increased ED admission due to a lack of access to care within the urgent care and primary care setting. O'Cathain et al. (2014) described the rationale behind increased admission rates within the ED due to the lack of availability of urgent or acute care appointments at a lower level of care, which resulted in the individual patients obtaining care in the ED, regardless of an acuity that was appropriate for ED care. If individuals perceive an inability to obtain care at a desired level, the individual will then obtain care at another level because the need for care to be rendered does not diminish based on a lack of availability. Hospital systems must ensure that access to care is available for the patient, if it is the hospital's desire to have the patient obtain care at an appropriate care level. The authors explained that the lack of access is a component of ED overcrowding. 150 health systems were subjects within the study, and the authors assessed the success of the studying by employing a three-phase mixed-methods approach, including avoidable admission rates, characteristics or ED and urgent cares settings, and the utilization of linear regression to explain avoidable ED admission rates. Quantifiable data was able to be collected through admission rates, and 82 interviews were completed with staff and patients to gather characteristics and categorization of why care was rendered in an urgent or ED care setting.

The study by O'Cathain et al. (2014) was consistent with other scholarly work and research who have identified access barriers in low acuity settings contributing to ED overcrowding and capacity management constraints. The author's depiction and findings that increasing access to lower acuity settings will help drive patients to obtain care at lower acuity levels, if appropriate, without the perception that the quality of care or accessibility is hindered at the primary care or urgent care setting. The study is limited, however, in that the human perception of quality of care and accessibility may not be dependent on the actual availability of services. Although hospital systems may improve the access to care in low acuity settings, such as the urgent care or primary care setting, does not mean that the patient will not perceive a higher level of care in the ED setting, which would not aid in the reduction of ED overcrowding.

Understanding additional components and barriers that may contribute to capacity management issues in the ED and inpatient setting is important to the field of health care. A health system cannot expect a patient to obtain care at an appropriate level, if that level of care is not accessible. The research study is relevant to hospital systems that are vertically integrated and include multiple levels of care obtainable by the patient. Further information is needed regarding the impact of urgent care settings, including third-party urgent care setting, and the potential impact low acuity settings have on the ED. Additional information would also contribute to a better understanding of which capacity management solution should be prioritized for implementation.

Pope et al. (2017) provided a case study utilizing 3 health systems to describe the decision-making process completed by ED physicians, ED nurses, managers, and inpatient doctors when deciding to change the level of care of a patient from the ED setting to the inpatient setting. The authors explained the rationale that inconsistent decision-making processes and non-clinical influences directly increased the rate in which patients were admitted to the inpatient setting, regardless of the medical need for additional care. Pope et al. (2017) explained that external factors, such as patients support system and community resources were large influencers in whether a clinician admitted a patient to the in-patient setting, as well as a 4-hour waiting period within the ED prior to a patient being admitted. The decision-making progress of admitting a patient was reviewed through semi structured interviewing techniques, which were then categorized within theoretical frameworks as to why a decision was being made. System culture, leadership, and processes all influenced the decision-making process, according to the authors. Qualitative data analysis was completed to group the interviewees opinions into theoretical frameworks around the aforementioned influences, while the interviewees were kept confidential and were interviewed separately.

Organizational management and organizational culture are a significant influencer when it comes to staff decision-making, which is consistent with other theorists in the scientific realm regarding organizational theory. Pope et al. (2017) addressed the human component that is a factor for hospital admittance from the ED, which contributes to inpatient overcrowding and inpatient boarding within the ED. The study supports the need for strong leadership within the ED to help aid clinical and non-clinical staff to make decisions regarding patient care according to the level of care needed, and to consider eternal factors, such a community resources, but to not heavily emphasize external factors when making decisions on admitting a patient. Pope et al. (2017) acknowledged that defining and fully understanding organizational structure and culture is logistically challenging, which present a limitation when depicting solutions to overcrowding in the inpatient setting.

Understanding the human component to the decision-making process regarding clinical matters and patient care is relevant to the health care field, due to the significant amount of decisions that are made that affect different levels of care. Pope et al.'s (2017) explanation of organizational culture and external influencers helps researchers and hospital administrators who may be designing processes to consider the human component to decision-making. However, further discussion and research is needed around organizational culture within a multi-hierarchal staff matrix, such as the ED, as research is limited or contains significant limitations.

Patient Experience External Factors

Kieft, de Brouwer, Franke, and Delnoij (2014) investigated the impact of patient experiences due to clinical interactions, and the perception of the quality of care based on the interaction. Kieft et al. (2014) described that patients often rate the quality of care received based on the interactions within clinical staff, such as nurses, and not based on the actual quality of the care rendered. If nurses, specifically, are not considered pleasant to the patient or the patient perceives that the nursing staff did not spend adequate time caring for the patient, then the patient is likely to rate the quality of care received lower than if the perception of the nurse's time was adequate. The authors promoted a rationale that the patient perception is not fully understood by the nursing staff, resulting in the nursing staff not being fully cognizant of the impact clinicians have on patient perception and patient satisfaction scores. The study assessed 26 nurses who were selected via purposeful sampling, and the authors outlined the progress of the study by utilizing descriptive qualitative research design and four different focus groups which consisted of interviews. Additionally, the authors assessed the nursing staff's understanding of the impact had on the patient experience by the individual nurse and the influencers that explained if that nurse did not feel as if adequate time could be spent with the patient, due to factors such as pressure to have high workloads.

Kieft et al.'s (2014) explanation of nurse perceptions, and the impact nursing and patient perceptions have on patient experience and patient experience scores, is consistent with other research in the health care field, including data provided by CAHPS surveys, that nursing staff who spend adequate time with patients are able to boost patient satisfaction scores and the perception the patient has regarding the quality of care rendered. The study is relevant to patient satisfaction surveys utilized in the health care field and by health systems when determining the questions and factors that impact a patent's perception of care. The creation of patient-centered care models allows for clinicians to be cognizant of the patient perceptions, so that quality of care is not hindered by a variable that may be independent by nature, but negatively affect the quality of care perception. However, the study was limited by the relatively small sample size and the lack of scientific research focusing on the clinician's understanding of the patient perception, as well as a saturation level was reached where new information was not obtained during the research phase (Kieft et al., 2014). Additionally, further emphasis on the variables that impact the patient when making decisions regarding quality of care will give better insight to clinicians when the clinician is rendering care, outside of the physical care component.

There is a correlation between patient satisfaction and the LWBS rate due to extended wait times within the ED (Pasupathy et al., 2017), as well as poorer clinical outcomes for the patient (Storm-Versloot et al., 2014). Patient satisfaction and clinical outcomes directly impact a hospital system's ability to be reimbursed for services (Thiels et al., 2016). Clinical perceptions and staff perceptions can contribute to the patient experience, and contribute to longer LOS.

Kieft et al.'s (2014) explanation that clinical staff perceptions of the time the staff spends with the patient directly impacts patient experience and the perception of the quality of care the patient receives is relevant to health care administrators when defining patient experience benchmarks and survey tools. This study is also relevant to clinicians who may not fully understand the impact the clinician has on the perceptions of the patient's satisfaction and quality of care. Patient experience and satisfaction are used frequently within the ED and inpatient setting. However, more information is needed to assess the different levels of clinician involvement, as clinician involvement can vary significantly. Additionally, more information is needed to assess the effects of multiple clinicians' encounters on patient perceptions, as single clinician interaction is rare within the ED setting. As strategies are designed to aid in capacity management, additional research regarding the variables that influence patient satisfaction are needed, as to not negatively impact patient satisfaction with implemented solutions.

Use of Queueing Theory

Queueing theory is primarily used in manufacturing processes, and is limited in use within healthcare. Due to the aforementioned, there is a gap in research of queueing theory being utilized within healthcare application. However, queueing theory looks at the different paths that an object travels throughout a system and may be helpful to regulate capacity management barriers based on statistics and differential equations that see patients as moving parts through a systematic and mechanic means (Armony et al., 2015). Capacity management barriers contribute to longer length of stay rates for patients (LOS), hospital systems seeing a higher rate of left without being treated (LWBT), and a reduction in clinical outcomes and higher mortality (Armony et al., 2015). Queuing Theory utilizes a Poisson process, the probability of an event occurring, and suggests that queue lines or processes of throughput have fluid limits and can be predicted through the use of mathematical equations (Heyde, 2001).

Routing algorithms can determine the optimal throughput of a patient by depicting the nodes of services in which the patient may travel. Erlang's use of queueing theory provides a mathematical approach to modeling possible pathways a patient may take within a health system, as well as barriers that may arise to disrupt a service node or a patient's throughput. Subsequent research and application utilizing Erlang's Queuing Theory offers support of the utilization of queueing theory in the hospital system setting in order to improve organizational performance and the increase in health care and patient demand (Bittencourt, Verter, & Yalovsky, 2018).

Conclusion

Capacity management within the ED and inpatient setting encompasses many different components and variables, including EMR processes/patient flow, LOS metrics, LWBS rates, inpatient boarding rates, patient satisfaction, access to lower levels of care, and a human decision-making component. Georgiou et al. (2013) discussed the importance of creating effective and efficient processes within the EMR reflective of the unique nature of the ED, including the impact of an effective EMR workflow system on the LOS and LWBS benchmarks. Emergency department (ED) abandonment or left without being seen (LWBS) rates are having detrimental effects on the ability for systems to service patients due to extended wait times, length of stay (LOS), within the ED and poor capacity management, which is a recognized gap but not widely researched (Pasupathy et al., 2017).

Efficiency in work processes must also include protocols to ensure that there is a consistency in how clinicians work within the ED. A lack of efficient processes and clinical attention can directly impact patient satisfaction scores (Kieft, 2014). Patient satisfaction is also negatively impacted by long waits and overcrowding, which results in patients not obtaining care in a timely fashion, which correlate to longer LOS and higher rates of LWBS (Chang et al., 2017). However, it is important for health systems to recognize that external factors may exist outside of the ED and inpatient setting. One external factor is accessibility within the urgent and primary care setting. If patients cannot utilize care within the urgent and primary care setting, the patient will obtain care where access is available, which results in the patient obtaining care in the ED, contributing to ED overcrowding and lengthened LOS (O'Cathain et al., 2014).

When assessing capacity management within the ED and inpatient setting, it is crucial for the setting to be assessed for internal and external variables, as well as additional impacts on the health systems. The inpatient setting controlling admissions from the ED directly relate to longer patient boarding within the ED setting (Chang et al, 2017). The longer patients boarding within the ED setting leads to higher rates of patient mortality, increased LOS for patients awaiting care or having care rendered, and higher LWBS rates (Chang et al, 2017). It is crucial to understand the factors that may impact an outcome, in this studies case the inpatient setting directly impacts the outcomes of the ED setting.

Thus, there is a gap of understanding in terms of the components that may negatively impact capacity management. There is a lack of knowledge regarding possible implementation solutions within the ED and inpatient setting that could aid in a reduction of LOS, LWBS, as well as a reduction in boarding rates. Through the implementation of possible solutions, a hospital system can begin to have a better understanding of how to manage capacity management within the emergent care and inpatient setting, as well as provide better access to care for patients.

Section 2: Research Design and Data Collection

Introduction

The purpose of this study was to examine the use of queueing theory in capacity management and the impact of queueing theory on LOS, LWBS rates, and boarding rates within the ED and inpatient setting. In this retrospective quantitative study, I assessed if there is a relationship between capacity management, the process of moving patients throughout the system, and a reduction in LOS rate, LWBS rate, and boarding rates within the ED.

I looked at the hospital system as a manufacturing system of moving parts, much like a manufacturing plant, which is where queueing theory is rooted. The patient represents the parts moving through the system with the completion of the process at patient discharge from the system. Barriers within the process, such as in departments like the ED or inpatient setting, can cause systematic disruption with the patient's journey through the system (Chang et al., 2017). The systematic disruption has a trickle-down effect on clinical outcomes and hospital reimbursement, and the impact of capacity management within the ED and inpatient setting on system outcomes has not been widely reviewed and analyzed (Chang et al., 2017). Capacity management allows for patients to move through the hospital system in the most effective and efficient manner to ensure the maximization of resources within the system.

In this section, I detail the research design and methods for this study, in which I analyzed a dataset consisting of longitudinal datasets of LOS from Inter-University

Consortium for Political Science and Social Research depicting patients' LOS from system admittance to discharge as a baseline prior to a system's use of capacity management. This was a quantitative study. Queueing theory capacity management data were accessed from simulation data from a queueing theory model for capacity management within a large, vertically integrated health system that depicts LOS and LWBS rates as well as patient boarding within the ED. The data did not display any patient health information (PHI) and followed all Health Insurance Portability and Accountability Act requirements, including de-identification. Within the research design and rationale section, I reviewed each of the research questions and provided a rationale for using linear regression and correlation to determine the relationship of the use of queueing theory on LOS rates, LWBS rates, and patient boarding. In the methodology section, I summarize the study population, sample, and sampling procedures and include the recruitment for the original study completed by the United States Department of Health and Human Services (2011) and Wiler et al. (2013).

Next, I review the instrumentation of the two studies, including methods to improve reliability and validity. The data analysis section addresses the details of data review and cleaning. In the final two sections, I discuss the threats to internal and external validity, including steps that were taken to minimize the threats.

Research Design and Rationale

In this study, I used three primary research questions:

RQ1: Is there a relationship between capacity management using queueing theory and LOS in the ED?

H_1-: There is a statistically significant difference between capacity management using queuing theory to reduce LOS in the ED.

H_{01}: There is not a statistically significant differences between capacity management using queuing theory to reduce LOS in the ED.

RQ2: Is there a reduction in the abandonment rate or LWB) rate when capacity management is used within the ED setting?

H_2: There is a statistically significant difference between capacity management using queuing theory to reduce LWBS in the ED.

H_{02}: There is not a statistically significant difference between capacity management using queuing theory to reduce LWBS in the ED.

RQ3: Is there a relationship between capacity management within the ED and inpatient setting and inpatient boarding rates within the ED?

H_3: There is a statistically significant difference between capacity management using queuing theory to reduce in-patient boarding rates in the ED.

H_{03}: There is not a statistically significant difference between capacity management using queuing theory to reduce in-patient boarding rates in the ED.

The first research question addressed the relationship between capacity management and the LOS rate when the system uses queueing theory, while the second question addressed abandonment rate, LWBS, when capacity management is implemented within the ED setting. The third question addressed the relationship between the inpatient and ED setting in regards to in-patient boarding rates within the ED setting. The relationships of the three research questions were determined by reviewing

LOS, LWBS, and boarding rates over time with data collected via an EMR system within multiple hospital systems where capacity management procedures have been implemented.

The independent variable was the number of patients who enter the ED or inpatient setting and began the process of capacity management. The dependent variables were LOS, LWBS or abandonment rate, and boarding rate within the ED. LOS, LWBS rate, and boarding rate were compared by analyzing the LOS, LWBS rate, and boarding rate of systems that use queueing theory for capacity management and systems that do not use queuing theory for capacity management.

The use of a correlational study design, with a quantitative approach, was appropriate for the study to assess if a relationship exists between the dependent and independent variables of the study. The use of secondary data was employed in accordance to the recommendations of Omair (2015) in order to determine an association between the variables. Correlational studies are also recommended when using secondary hospital system data from EMRs when comparing multiple factors from the EMR (Omair, 2015). Because of the use of historical data, as well as data collected over multiple years, correlational study design may help to assess the relationship between the independent and dependent variables of the study. The design is an ex-post facto design that used a longitudinal design within the correlational study approach, which is a nonexperimental design process.

Correlational studies are used primarily when comparing national or international data on a large scale but are being increasingly used when reviewing hospital system data where EMR data are being analyzed (Omair,2015). One area of concern with correlational studies is the emergence of ecological fallacies. Due to the nature of the study, ecological fallacies could result in positive relationships due to external factors, including the hospital system's community environmental or societal factors. It is important to note that ecological fallacies could create validity constraints within the study, and analyzing confounding factors is required (Omair, 2015).

I used secondary data from the National Hospital Ambulatory Care Survey as well as patient flow data where queueing theory has been implemented as a method of capacity management for comparison purposes. The data are considered archival data, as to allow for data collection over a larger data pool and over a greater time period. Secondary data are beneficial due to the low burden of cost as well as larger samples existing that are more representative of the population (Johnston, 2014). The use of secondary research also allows a varying perspective to assess the archival dataset, which can develop increased knowledge from the data. A disadvantage to using secondary data is that the collection of the data cannot be confirmed to have gone through proper vetting processes to ensure unbiased and proper collection methods (Johnston, 2014). A second disadvantage is that historical data may be outdated or have conditions applied that may create validity constraints with the study as well as an inability to conduct follow-up with the participants (Heaton, 2008).

Methodology

Population

For this secondary data analysis, I used data collected by the National Hospital Ambulatory Medical Care Survey (NHAMCS), which surveyed 353 hospital systems inpatient settings and 431 EDs across the continental United States("NHAMCS, 2008", 2011). Patient record forms (PRF) were completed at a rate of 93.1% unweighted completion rate, while 34, 134 (N = 34,134) completed, individual PRFs were collected ("NHAMCS, 2008", 2011). The NHAMCS collected data from patients who used health systems that were not federally categorized and had services rendered in the ED or inpatient setting classified as short-stay or general admission adult care. The second set of secondary data consisted of a population (N= 87,705) who entered a large, urban hospital system's ED over 2008 in Chicago, Illinois, with N = 647 excluded due to missing data (Wiler et al., 2013). The second set of secondary data included data where queueing theory was implemented for the purpose of patient flow and capacity management. The third dataset came from the NEDS and used the dataset from 2008 to ensure a comparable dataset to the datasets collected within the other studies. The dataset consisted of a population of 980 EDs and a population of N = 28,861,047 unweighted ("Introduction to the NEDS 2016", 2016).

Power Analysis

The statistical power analysis that was completed for this study was conducted using G*Power and SPSS and will represent a post hoc power analysis due to the analysis of an already published secondary dataset (see Faul, Erdfelder, Buchner, & Lang, 2009).

An a priori power analysis was appropriate for this study, where $\propto = .05$ and power $(1 - \beta \text{ error probabaility})$ = .8, while the effect size was set at a medium effect size, f^2= .15 ("Power analysis for two-group independent sample t-test | G*Power Data Analysis", 2019). The $(1 - \beta)$ represents the beta error probability for the study and determined the probability of an incorrect null hypothesis (Faul et al., 2009). The sample sizes used for the analysis was N = 34,134, which reflected complete data from the three secondary datasets.

The use of the aforementioned statistical parameters falls within the guidelines of the conventional parameters of power analysis. The study satisfied the parameters set forth by Creswell (2017), which included determining the significance level α, sample size (N), effect size (f^2), and expected differences in the means between the control and interventional groups expressed in standard deviation units for the variables that were assessed within the study.

Sampling and Sampling Procedures

The target population consisted of two studies, hospital systems utilizing capacity management without queueing theory and a system utilizing queueing theory for capacity management. The sampling for the first dataset was comprised of a population where queueing theory was not implemented within the systems with the system's capacity management processes.

Patients surveyed within the systems where queueing theory was not utilized for capacity management were within the following parameters

- Adult hospital system patients aged 18 years or older;

- Patients with stays < 30 days in the inpatient hospital setting, categorized as short-stay patients;
- Patients who participated in a personal exchange verbally and in-person with a medical professional within the care setting;
- Patients who were admitted via the ED setting.

Patients surveyed within the systems where queueing theory was utilized for capacity management were within the following parameters

- Adult hospital system patients aged 18 years of older;
- Patients with stays < 30 days in the inpatient hospital setting, categorized as short-stay patients;
- Patients who entered the ED care setting and were checked into the waiting queue of the ED;
- Patients with an emergency severity index triage acuity of a 3 or higher.

In the dataset collected during the NHAMCS survey (2011), 353 hospital systems inpatient settings and 431 EDs across the continental United States met the eligibility requirements for the inpatient and ED data collections procedures. The sampling was completed within the continental US and the District of Columbia. The sampling was surveyed over the 2008 calendar year defined from January 1, 2008 to December 31, 2008 ("NHAMCS, 2008", 2011). Patients were excluded if data was incomplete or missing, or if the patient was within the system for > 30 days.

In the second study, Wiler et al. (2013), sampled a population size of n= 87,705, with n= 647 excluded due to incomplete data. The sample included data collection at the following patient interval timestamps arrival time, emergency service index triage acuity of a 3 or higher ranking, ED bed placement time, patient time to LWBS, total treatment time, and ED boarding time (Wiler et al., 2013). It should be noted that a higher acuity is considered a 1 or 2, while a lower acuity is considered a 4 or 5 within the Emergency Severity Index (ESI) ("Emergency Severity Index (ESI)", 2019). The data was collected via EMR data collection. The sample was collected during the 2008 calendar year defined from January 1, 2008 to December 31, 2008 (Wiler et al., 2013).

Procedures for Data Collection

The collection of the secondary data for the first study was collected by the United States Department of Health and Human Services (DHS), Centers for Disease Control and Prevention, and the National Center for Health Statistics. The data was collected via the NHAMCS ("NHAMCS, 2008", 2011). The data was reviewed for quality assurance by the National Center for Health Statistics and is available via the ICPSR. The data is archived by the National Archive of Computerized Data on Aging (NACDA), the aging program within ICPSR.

The collection for the second dataset was collected via the University of Colorado School of Medicine utilizing EMR inputs from an academic, adult-only hospital system in Chicago, Illinois (Wiler et al., 2013). The data was assessed for quality assurance and validity via the Division of Emergency Medicine within the Washington University in St. Louis School of Medicine, the Department of Decision Science and Managerial Economics within the Chinese University of Hong Kong, and the Department of Information Systems and Operations Management within the University of Auckland

(Wiler et al., 2013). The data was archived within the University of Colorado Medical School in Aurora, Colorado. A third dataset was obtained from the Agency for Healthcare Research and Quality (AHRQ) and utilizes the NEDS survey. The NEDS dataset included data from the HCUP State Emergency Department Databases (SEDD) and the State Inpatient Databases.

I obtained the NHAMCS dataset from ICPSR, the emergency department dataset from the University of Colorado Medical School, and the 2008 NEDS dataset from the AHRQ data request process. All data requested went through the mandatory Confidential Information Access Request process.

Instrumentation and Operationalization of Constructs

Queueing theory. The *M*/*M/r* /s + *M*(*n*) Queueing theory model for Call Centers, with adaptation, has the ability to best describe ED patient flow, including patients who leave without being seen (LWBS) (Whitt, 2005). The variability of highly volatile or chaotic systems, such as a health system, where multiple patients are rendered services on a parallel track allow for the *M*/*M/r* /s + *M*(*n*) Queueing theory model to best accommodate the data collected within the systems with adaptation (Whitt, 2005).

Instrumentation assumptions for queueing theory model. *M*(*n*) is adjusted to accommodate the patient waiting time tolerance, which is derived from the Weibull distribution. The Weibul distribution is utilized for life modeling where variables cannot be fully predicted due to the individual parameters of the subject, in this case the parameters of waiting for each individual patient (Cohen, 1965). The Weibull distribution was determined by the equation $f(x;\gamma,\sigma) = \frac{\sigma}{\gamma}\frac{x}{\gamma}^{\sigma-1} e^{-}$ where γ and σ are the location and scale distribution where a mean time tolerance is 10.89 hours and location 11.68 hours (Whitt, 2005). This study will utilize the Weibull distribution of .46, per prior validation. *s* defines the total number of patients who will undergo an evaluation, but once capacity for the system is reached the ambulance diversion protocol is initiated and patients are diverted to other systems via transport services. In order to accommodate walk-in patients, the model capacity is increased to accommodate the additional volume for walk-in patients, which has been validated by other studies (Allon, Deo & Lin, 2013). *r* was set at a fixed rate for total amount of treatment spaces, regardless of fluctuations a system may make, including the closing of ED treatment spaces during low usage times. *r* is validated due to the treatment spaces being readily available if needed and not permanently closed.

Validation. The primary testing, utilizing the instrumentation time, took place between 10:00 AM and 12:00 PM at the 1% significance level, with validation occurring by testing a moderate patient arrival time, 8:00 AM to 10:00 AM) and the lowest arrival time (4:00 AM to 6:00 AM) compared to the highest volume time (10:00 AM to 12:00 PM) (Wiler et al., 2013). Stationarity assumptions are required to ensure validity for queueing theory models, which means mean, variance, and autocorrelation do not change ("Stationarity", 2019). The observation confirmed the stationarity assumption is validated and that capacity management, LWBS, can be analyzed (Wiler et al., 2013). Table 1 shows the queueing theory model inputs.

Table 1

Queueing theory Model Inputs

Queueing model term	Call center application	Modification for ED system
First *M*	Interarrival times between calls to the system assumed to follow an exponential distribution. *	Time between ED arrivals.
Second *M*	Time speaking to call center agent follows an exponential time distribution.	Treatment time (including boarding).
r	Number of agents available to take calls.	Total ED treatment space (bed) capacity.
s	Maximum capacity of call center to accommodate calls.	Waiting area capacity (i.e., maximum number of patients who will wait for evaluation).
M(n)	Caller waiting time tolerance distribution approximated by an exponential distribution as a function of total number of callers waiting	Patient waiting time tolerance to see provider calculated from a Weibull distribution .46
*		

Note. *Arrivals occur with a known average rate and the number of arrivals in some fixed time period are independent of the number of arrivals in a nonoverlapping time period. Adapted from "An Emergency Department Patient Flow Model Based on Queuing Theory Principles" by J. Wiler, E. Bolandifar, R. Griffey, R. Poirier, & T. Olsen, 2013, *Academic Emergency Medicine*, *20*(9), pp. 939-946.

NHAMCS variables. The NHAMCS was utilized as an instrument for data collection via paper survey. The NHAMCS is designed to collect data on the utilization and provision of ambulatory care services in hospital emergency and outpatient departments ("NAMCS/NHAMCS - About the Ambulatory Health Care Surveys", 2019). Blank responses are not considered complete data and are excluded from the dataset. Systems who participated in the Queueing theory model excluded themselves from national surveys in 2008. Table 2 shows the NHAMC survey variables from the dataset.

Table 2

NHAMC Survey Variables

Variable	Survey label	Inputs
LOV	Length of stay.	Numerical input by patient or “Blank”
LEFTBMSE	Left before being seen for medical exam.	“Yes” “No” “Blank”
BOARD	Admitted patients boarded in the ED> 2 hours.	“Yes” “No” “Blank”

Note. Adapted from the NHAMC survey” by the National Hospital Ambulatory Medical Care Survey: 2008 Emergency Department Summary Tables. (2019). Retrieved from https://www.cdc.gov/nchs/data/ahcd/nhamcs_emergency/2008_ed_web_tables.pdf

Nationwide Emergency Department Database (NEDS)

The AHRQ implemented the Healthcare Cost and Utilization Project (HCUP) which has collected comprehensive data for emergency department utilization. The NEDS was constructed using the HCUP SEDD and the state inpatient databases

("Introduction to the NEDS 2016", 2016). The 2008 NEDS collection did not consist of EDs within the state of Illinois, which is where the queueing theory dataset had been collected ("Introduction to the National Emergency Department Sample (NEDS) 2016", 2016).

Study Variables

Dependent Variable

The dependent variables for the study consisted of LOS, LWBS and boarding rate within the ED care setting. The data was collected via three secondary sources. The first set of data consisted of data collected by the NHAMC survey, as well as the third dataset NEDS, which consisted of systems where a capacity management was utilized, but the queueing theory model was not utilized. The second set of secondary data came from a health system where the Queuing Theory model for capacity management was being utilized and has been utilized over a one-year period. The dependent variable datasets for capacity management without a queueing theory model and with a queueing theory model were collected over the same time period, as to ensure an adequate comparison and analysis. The data was collected from EMR records and the validated NHAMC and NEDS surveys. Boarding rate for this study were defined as LOS > 2 hours for admitted ED patients who have been admitted into the inpatient setting. LOS is represented by the length of time in which the subject is present within the ED care setting from the point of check-in to discharge. LWBS is representative of subjects who leave the care setting post-check-in, but prior to having medical care rendered by a medical professional in accordance to the medical necessity determined by the subject’s acuity.

Independent Variable

Queueing theory represented the intervention within this study with the independent variable being systems that utilize queueing theory and systems that do not utilize Queuing Theory for capacity management. The purpose of the utilization of the theory was to maximize the number of patients in which a system can process through the ED care setting reducing patients who leave without being seen. Due to the inability to accurately predict subject that may walk-in to the ED setting, capacity parameters within the queueing theory model were increased and the increase of the parameters had been validated within other studies (Allon, Deo & Lin, 2013). Table 3 shows the study variables used within this study.

Table 3

Study Variables

Variable type	Variable	Level of measurement	Potential response	Data source
Dependent	LOS	Continuous	Numerical entry	NHAMC/EMR
Dependent	LWBS	Nominal	Yes/No	NHAMC
Dependent	Boarding Rate	Nominal	Yes/No	NHAMC
Independent	Non queueing theory capacity management system patients	Continuous	Numerical entry	NHAMC
Independent	Queuing theory utilized capacity management system patients	Continuous	Numerical entry	EMR

Data Analysis Plan

This study examined the use of Queueing theory in capacity management and the impact of Queueing theory on length of stay (LOS), left without being seen (LWBS) rates, and boarding rates within the emergency department (ED) and inpatient setting. This was a retrospective quantitative analysis assessing if there is a relationship between capacity management, the process of moving patients throughout the system, and a reduction in LOS rate, LWBS rate, and boarding rates within the ED. The software utilized for this study was G*Power and SPSS version 24. The statistical analysis was linear regression.

Analysis Plan for Research Questions

RQ-Quantitative: Is there a relationship between capacity management utilizing queueing theory and Length of Stay (LOS) in the emergency department (ED)?

H_1- There is a statistically significant difference between capacity management utilizing Queuing Theory to reduce LOS in the ED.

H_{01}- There is not a statistically significant differences between capacity management utilizing Queuing Theory to reduce LOS in the ED.

RQ-Quantitative: Is there a reduction in the abandonment rate or left without being seen (LWBS) rate when capacity management is utilized within the ED setting?

H_2- There is a statistically significant difference between capacity management utilizing Queuing Theory to reduce LWBS in the ED.

H_{02}- There is not statistically significant difference between capacity management utilizing Queuing Theory to reduce LWBS in the ED.

RQ-Quantitative: Is there a relationship between capacity management within the ED and inpatient setting and inpatient boarding rates within the ED?

H_3- There is a statistically significant difference between capacity management utilizing Queuing Theory to reduce in-patient boarding rates in the ED.

H_{03}- There is not a statistically significant difference between capacity management utilizing Queuing Theory to reduce in-patient boarding rates in the ED.

Analysis Plan

The first research question addressed whether there was a relationship between capacity management utilizing queueing theory and Length of Stay (LOS) in the emergency department (ED) for the dataset where capacity management is controlled via a queueing theory model and LOS within systems where a queueing theory is not utilized. The assessment of the relationship was completed by competing a linear regression analysis with the parameters and assumptions detailed within this section.

The second research question assessed if there was a relationship in the abandonment rate or left without being seen (LWBS) rate when capacity management with queueing theory is utilized within the ED setting compared to when capacity management is not utilized. The relationship was defined by completing a linear regression assessing LWBS within systems that utilize queueing theory compared to LWBS within systems that do not utilize queueing theory.

The third research question assessed the boarding rates of systems that utilized queueing theory and the boarding rate of systems where queueing theory was not utilized within the health system. The third research questions followed the same procedures of research one and two and consisted of a data analysis utilizing linear regression.

A linear regression analysis was completed. The data is continuous or nominal in nature, and the purpose of this study was to assess if two variables have a relationship. The independence of residuals was completed via a regression analysis and viewing the Durbin Watson (DW) statistic. The DW assessed the autocorrelation of the analysis, and whether the correlation is positive or negative. A value of 0-2 depicted a positive autocorrelation, while a value between 2-4 will indicated a negative correlation. If the DW displayed a value of 2, there was not an autocorrelation. Model significance was reviewed via assessing if $p<.05$ The model ran was a linear regression with a confidence interval (CI) of 95%. A T-test analysis assessed if the population is similar and therefore has similar means. If the means are statistically different, then an assumption could be created that suggest that the population was different. I then assessed the adjusted R^2, which determined the percentage of the variance in the dependent variable explained by the independent variables. The adjusted R^2 was completed in SPSS and is a more conservative R-value. The adjusted R^2 was assessed for other predictors within the model and is representative of the R^2 which is the correlation coefficient that assesses the strength of the relationship within the model. ANOVA output was also reviewed after the statistical analysis to assess the analysis of means for the variables. A statistically significant finding occurred if the significance is <.05. Model coefficients were then reviewed. The coefficient output depicted the significance the variable had in regards to the impact on the outcome variable. The beta coefficient explained the degree of change in the outcome variable for every one unit of change determined by the predictor variable. The null hypotheses for all three research questions was rejected if $p<.05$.

Threats to Validity

Internal Validity

Internal validity is the process in which the results of the study is attributable to the independent variable and does not have confounding factors or variables outside of the research. Minimizing exposure within the study can assist in minimizing internal validity threats, including randomizing the study (Dusetzina, Brookhart, & Maciejewski, 2015). Datasets were collected for the national studies via submittal and collection from hospital systems. The independent procedures for the hospital system collecting LOS, LWBS, and boarding rates cannot be fully confirmed due to the difference in EMR systems and independent procedures for collection within the systems. The datasets were randomized with helps assert internal validity within this study. EMRs are considered to be the gold standard for the collection of clinical data and health outcomes, but ensuring that the collection has a proper methodology and procedural practice will help ensure internal validity. (Gregory & Radovinsky, 2012).

Wiler et al. (2013), explained in the original study that the data collection process, when observing or collecting data within a queueing theory model, is unpredictable and unmanageable. As previously noted, systems activate diversion protocols at different points that are dependent on the individual systems. However, the Queuing Theory model was adapted to ensure that patients who walk into the ED system are still accounted for, since walk-in patients are not controlled within the parameters or scope of diversion protocols, which was previously validated (Allon, Deo, & Lin, 2013). The adjustment ensured that patient data was not improperly excluded due to being collected outside of the diversion protocol, and that the collection process was unbiased based on how the patient entered the ED system. The following characteristics were used: adult hospital system patients aged 18 years of older, patients with stays < 30 days in the inpatient hospital setting categorized as short-stay patients, patients who entered the ED care setting and were checked into the waiting queue of the ED, and patients with an emergency severity index triage acuity of a 3 or higher.

External Validity

In order to be eligible for the study, the patient must have met the criteria of being an adult at least 18 years of age, the patient has a ESI triage acuity of a 3 or higher, and must have been classified a short-stay patient. External validity is based on the factors and parameters that a study can be reproduced and generalized to a larger population base, including interaction of the causal relationship over treatment variations (Petursdottir & Carr, 2018). Although the study did not include pediatric patients, the simulation or flow paths a pediatric patient would encounter would be similar to the adult counterpart. However, the lack of pediatric patients should be noted. The questions of external validity were more of a concern due to the study excluding patients with a low ESI acuity, 4 or 5. The patients who presented with criteria meeting a 4 or 5 ESI acuity, when triaged, require medical resources that are often available in a prompt/urgent care or primary care office ("Emergency Severity Index (ESI)", 2019). The ED population cannot be controlled, so limiting research to ESI acuities of a 3 or higher could create external validity constraints, and would not be fully reflective of the ED population. The ESI acuity benchmarks and criteria also differ for pediatric patients ("Emergency Severity Index (ESI)", 2019). However, queueing theory examines all possible patient flow paths, and although a patient may not meet the acuity requirements, the patient would still flow through the system and have care rendered. The external validity constraints should be able to be mitigated due to patient care still being rendered and following patient flow paths within the internal system.

Ethical Procedure Information

This study did not involve experimentation on human participants, and it was limited to retrospective review of secondary data collected during a previous study done by Wiler et al. (2013). All data had been deidentified and did not share patient names, social security numbers, birth dates, or medical record numbers (MRN) within any secondary data that will be utilized. The Wiler et. al (2013) study did not share modalities or diagnoses, which could be utilized to identify a subject with knowing the involved hospital systems, while the national surveys did not provide hospital information or location of patients involved. No personal information or hospital identifiers were used in describing the study or the results. The IRB approval number is 07-10-19-0721885.

Summary

In this study, I used a quantitative approach of secondary data sources to examine the utilization of queueing theory on capacity management in regards to LOS, LWBS, and boarding rates in the emergent care setting. I aimed to identify the relationship of hospital systems who utilized queueing theory compared to systems who did not utilize queueing theory when managing patient flow and capacity management by analyzing the system's LOS, LWBS, and boarding rates. The study was limited to patients who presented in the ED setting, who were 18 years of age and older, obtained an ESI triage acuity score of a 3 or higher, and were not considered long-stay patients.

Section 3: Presentation of the Results and Findings

Introduction

The purpose of this study was to examine the use of queueing theory in capacity management and the impact of queueing theory when used within capacity management on LOS rates, LWBS rates, and boarding rates within the ED and inpatient setting. In this study, I assessed if there was a relationship between capacity management, the process of moving patients throughout the system, and a reduction in the aforementioned rates when queueing theory is initiated within the ED and inpatient setting compared to traditional processes across systems within the continental United States. Secondary data were used and a linear regression statistical analysis with an independent *t* test was used to answer the study's research questions.

The research questions and the hypotheses that were tested were as follows:

RQ-Quantitative: Is there a relationship between capacity management utilizing queueing theory and Length of Stay (LOS) in the emergency department (ED)?

H_1- There is a statistically significant difference between capacity management utilizing Queuing Theory to reduce LOS in the ED.

H_{01}- There is not a statistically significant differences between capacity management utilizing Queuing Theory to reduce LOS in the ED.

RQ-Quantitative: Is there a reduction in the abandonment rate or left without being seen (LWBS) rate when capacity management is utilized within the ED setting?

H_2- There is a statistically significant difference between capacity management utilizing Queuing Theory to reduce LWBS in the ED.

H_{02}- There is not statistically significant difference between capacity management utilizing Queuing Theory to reduce LWBS in the ED.

RQ-Quantitative: Is there a relationship between capacity management within the ED and inpatient setting and inpatient boarding rates within the ED?

H_3- There is a statistically significant difference between capacity management utilizing Queuing Theory to reduce in-patient boarding rates in the ED.

H_{03}- There is not a statistically significant difference between capacity management utilizing Queuing Theory to reduce in-patient boarding rates in the ED.

A linear regression analysis was completed because the data were continuous or nominal in nature, and the purpose of the study was to determine if two variables have a relationship. The independence of residuals was completed via a regression analysis and viewing the DW statistic. The DW assessed the autocorrelation of the analysis and whether the correlation was positive or negative. A value of 0 to 2 depicted a positive autocorrelation, while a value between 2 to 4 indicated a negative correlation. If the DW displayed a value of 2, there was no autocorrelation. Model significance was reviewed via assessing if $p < .05$. The statistical test ran within SPSS was linear regression with a CI of 95%. A *t*-test analysis assessed if the population was similar and therefore had similar means. If the means were statistically different, then an assumption was created that suggested that the population is different. The adjusted R^2, which determined the percentage of the variance in the dependent variable, is explained by the independent variables.

The adjusted R^2 was also completed in SPSS and is a more conservative *R*-value. The adjusted R^2 was assessed for other predictors within the model and is representative of the R^2, which is the correlation coefficient that assesses the strength of the relationship within the model. ANOVA output assessed the analysis of means for the variables. A statistically significant finding occurred if the significance was <.05. Model coefficients were then reviewed. The coefficient output depicted the significance the variable had in regards to the impact on the outcome variable. The beta coefficient then explained the degree of change in the outcome variable for every unit of change determined by the predictor variable. The null hypotheses for all three research questions was rejected if $p < .05$.

Collection of Secondary Data

The collection of the secondary data for the first study was conducted by the United States DHS, Centers for Disease Control and Prevention, and the National Center for Health Statistics. The data were collected via the NHAMCS ("NHAMCS, 2008", 2011). The data were reviewed for quality assurance by the National Center for Health Statistics and are available via the ICPSR. The data were archived by the National Archive of Computerized Data on Aging, the aging program within ICPSR. The collection for the second dataset was conducted via the University of Colorado School of Medicine using EMR inputs from an academic, adult-only hospital system in Chicago, Illinois (Wiler et al., 2013). The data were assessed for quality assurance and validity via the Division of Emergency Medicine within the Washington University in St. Louis School of Medicine, the Department of Decision Science and Managerial Economics within the Chinese University of Hong Kong, and the Department of Information Systems and Operations Management within the University of Auckland (Wiler et al., 2013). A third dataset was obtained from the AHRQ and uses the NEDS survey. The NEDS dataset includes data from the HCUP SEDD and the state inpatient databases.

The data were combined within SPSS and were differentiated by the two datasets that did not include systems that used queueing theory for capacity management, NHAMCS and NEDS, per the queueing theory dataset that specifically indicated exclusion from national surveys for the 2008 collection year.

The secondary data analysis used data collected by the NHAMCS , which surveyed 353 hospital systems inpatient settings and 431 EDs across the continental United States ("NHAMCS, 2008", 2011). PRFs were completed at a rate of 93.1% unweighted completion rate, while 34,134 (N = 34,134) completed, individual PRFs were collected ("NHAMCS, 2008", 2011). The NHAMCs collected data from patients who used health systems that were not federally categorized and had services rendered in the ED or inpatient setting classified as short-stay or general admission adult care. The second dataset came from the NEDS and used the dataset from 2008 to ensure a comparable dataset to the datasets collected within the other studies. The dataset consisted of a population of 980 EDs and a population of $N = 28{,}861{,}047$ unweighted ("Introduction to the NEDS 2016", 2016). The third set of secondary data consists of a population (N = 87,705) who entered a large, urban hospital system's ED over 2008 in Chicago, Illinois, with *n* = 647 excluded due to missing data (Wiler et al., 2013).

Study Demographics and Parameters

Patients surveyed within the systems where queueing theory was not used for capacity management were within the following parameters:

- Adult hospital system patients aged 18 years or older;
- Adult patients male and female;
- Patients with stays < 30 days in the inpatient hospital setting, categorized as short-stay patients;
- Patients who participated in a personal exchange verbally and in-person with a medical professional within the care setting; and
- Patients who were admitted via the ED setting.

Patients surveyed within the systems where queueing theory was used for capacity management were within the following parameters:

- Adult hospital system patients aged 18 years of older;
- Adult patients male and female;
- Patients with stays < 30 days in the inpatient hospital setting, categorized as short-stay patients;
- Patients who entered the ED care setting and were checked into the waiting queue of the ED; and
- Patients with an emergency severity index triage acuity of a 3 or higher.

Results

An a priori power analysis was appropriate for this study and therefore completed. An alpha of .05 and power = .8 was used, while the effect size was set at a medium effect size of f^2= .15. From the power analysis, a sample size of at least 343 was required to meet the parameters of the study. The sample size required was 343, which is well below the secondary sample size per the data collection parameters. Therefore, I was able to proceed reviewing LOS, LWBS, and boarding rates for systems using traditional processes for capacity management and systems using queueing theory for capacity management with a CI of 95%. Figure 1 depicts the G*Power analysis of the study.

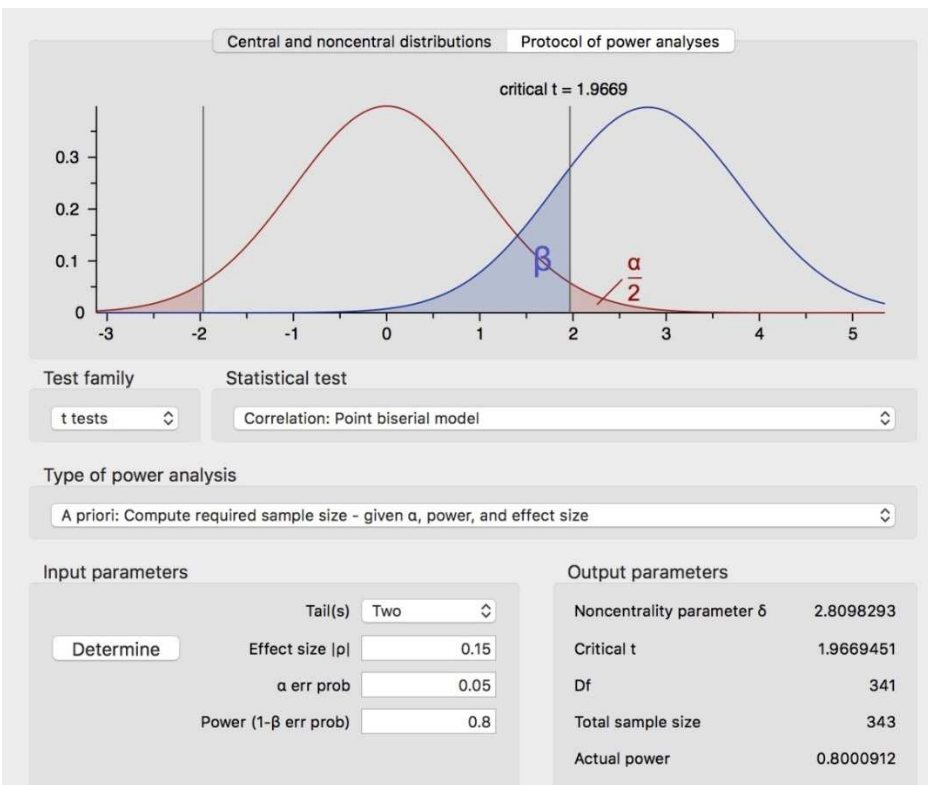

Figure 1. G*Power analysis. G*Power analysis showing secondary data sample size met the requirements and parameters required.

Length of Stay in the Emergency Department

LOS data were analyzed to review health systems where LOS was collected within systems that did not use queueing theory for capacity management compared to systems where queueing theory was used for capacity management within the inpatient and ED setting. A linear regression analysis was completed using SPSS Version 24. The dependent variable of the analysis consisted of the LOS data from hospital systems where queueing theory was not used for capacity management, while the independent variable consisted of LOS data where queueing theory was used within the system. An independent sample *t*-test analysis assessed the variances of the sample, which is depicted in Figure 3. Figure 2 represents the sample size analyzed for the secondary data representing LOS.

	LOS identifier Q v NQ	N	Mean	Std. Deviation	Std. Error Mean
LOS data complete	NQ LOS	34134	201.6019	215.25060	1.16507
	Q LOS	32423	207.4072	210.10147	1.16682

Figure 2. Sample size data for LOS dataset. Group statistics and sample size for LOS.

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
LOS data complete	Equal variances assumed	10.469	.001	-3.519	66555	.000	-5.80533	1.64992	-9.03916	-2.57149
	Equal variances not assumed			-3.521	66505.732	.000	-5.80533	1.64889	-9.03715	-2.57350

Figure 3. Independent sample *t*-test LOS. Independent *t* test reviewing LOS dataset for health systems using queueing theory for capacity management and health systems not using queueing theory for capacity management.

The analysis review for the LOS independent sample *t* test resulted in the Levene's Test for Equality of Variances being higher than .05. It is assumed that there are equal variances and the analysis results are depicted within the first row of figure 3. The *p*-value for the two-tailed significance resulted in a *p*-value <.05 at .001, which shows a significance difference between LOS of health systems using queueing theory for capacity management and health systems not using queueing theory for capacity management.

A linear regression analysis was completed comparing the independent variable, LOS in health systems not utilizing queueing theory for capacity management, compared to the dependent variable, LOS in health systems utilizing queueing theory for capacity management. Figure 4 represents the model summary and the adjusted R^2, while figure 5 represents the results of the ANOVA test within the linear regression analysis. The ANOVA test depicted the significance of the analysis, while figures 5 and 6 reviewed the beta coefficient and the linear regression residuals for the LOS dataset.

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.004[a]	.000	.000	210.759	.000	.515	1	32421	.473	1.554

a. Predictors: (Constant), Length of visit utilizing queueing theory

b. Dependent Variable: Length of visit (minutes)

Figure 4. Model summary for linear regression. Linear regression model summary depicting the R^2 and significance for the LOS dataset.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	22862.060	1	22862.060	.515	.473[b]
	Residual	1.440E+9	32421	44419.145		
	Total	1.440E+9	32422			

a. Dependent Variable: Length of visit (minutes)

b. Predictors: (Constant), Length of visit utilizing queueing theory

Figure 5. ANOVA test. Linear regression ANOVA summary depicting the significance for LOS dataset.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	198.969	1.645		120.974	.000	195.745	202.192
	Length of visit utilizing queueing theory	.004	.006	.004	.717	.473	-.007	.015

a. Dependent Variable: Length of visit (minutes)

Figure 6. Test of Coefficient. Linear regression Coefficients summary depicting the Beta and significance for LOS dataset.

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	198.97	210.22	199.80	.840	32423
Residual	-218.758	2679.766	.000	210.755	32423
Std. Predicted Value	-.983	12.411	.000	1.000	32423
Std. Residual	-1.038	12.715	.000	1.000	32423

a. Dependent Variable: Length of visit (minutes)

Figure 7. Test of Residual statistics. Linear regression results depicting the residuals compared to the sample size for the LOS dataset.

The model summary within figure 4 shows that the adjusted R^2 is .000. The analysis shows that 0% of the variance of the dependent variable can be explained by the independent variable. While the Durbin Watson statistic at 1.554 depicted a positive autocorrelation between the variable and the degree of change between the variables, the beta coefficient, showed that there was a change of .004. The ANOVA table within figure 5 showed p>.05 at .473. Due to the findings, the null hypothesis, H_{01}- there is not a statistically significant differences between capacity management utilizing Queuing

Theory to reduce LOS in the ED, could not be rejected. Therefore, it can be concluded that there is not significant difference between LOS in hospital systems that utilize queueing theory for capacity management within the ED compared to LOS in hospital systems that do not utilize queueing theory for capacity management within the ED. However, it cannot be rejected that there is a positive autocorrelation between LOS in health systems utilizing queueing theory for capacity management and LOS in health systems not utilizing queueing theory for capacity management.

Left Without Being Seen in the Emergency Department

Left without being seen (LWBS) data was analyzed to review health systems where LWBS was collected within systems that did not utilize queueing theory for capacity management compared to systems where queueing theory was utilized for capacity management within the inpatient and ED setting. A linear regression analysis was completed utilizing SPSS version 24. The dependent variable of the analysis consisted of the LWBS data from hospital systems where queueing theory was not utilized for capacity management, while the independent variable consisted of LWBS data where queueing theory was utilized within the system. An Independent Sample T-Test analysis assessed the variances of the sample, which is depicted in figure 9. Figure 8 represents the sample size analyzed for the secondary data representing LWBS.

	LWBS identifier	N	Mean	Std. Deviation	Std. Error Mean
LWBS data complete	LWBSQ	33424	1.78	.420	.002
	LWBSNQ	34134	1.98	.124	.001

Figure 8. Group statistics and sample size for LWBS. Sample size data for LWBS dataset.

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
LWBS data complete	Equal variances assumed	48097.912	.000	-87.335	67556	.000	-.207	.002	-.212	-.203
	Equal variances not assumed			-86.567	39070.530	.000	-.207	.002	-.212	-.202

Figure 9. Independent sample T-Test LWBS. Independent T-Test reviewing LWBS dataset for health systems utilizing queueing theory for capacity management and health systems not using queueing theory for capacity management.

The analysis review for the LWBS Independent Sample T-Test resulted in the Levene's Test for Equality of Variances being higher than .05. It is assumed that there are equal variances and the analysis results are depicted within the first row of figure 9. The P-value for the two-tailed significance resulted in a p-value <.05 at .000, which shows a significance difference between LWBS of health systems utilizing queueing theory for capacity management and health systems not using queueing theory for capacity management. Figure 10 represents the model summary and the adjusted R^2, while figure 11 represents the results of the ANOVA test within the linear regression analysis. The ANOVA test depicted the significance of the analysis, while figures 12 and 13 reviewed the beta coefficient and the linear regression residuals for the LOS dataset.

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.012[a]	.000	.000	.420	.000	4.747	1	33422	.029	.052

a. Predictors: (Constant), Left before medical screening exam

b. Dependent Variable: Left without being seen utilizing queueing theory

Figure 10. Model summary for linear regression. Linear regression model summary depicting the R^2 and significance for the LWBS dataset.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.837	1	.837	4.747	.029[b]
	Residual	5895.278	33422	.176		
	Total	5896.115	33423			

a. Dependent Variable: Left without being seen utilizing queueing theory

b. Predictors: (Constant), Left before medical screening exam

Figure 11. ANOVA test. Linear regression ANOVA summary depicting the significance for LWBS dataset.

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations		
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part
1	(Constant)	1.697	.037		46.072	.000	1.625	1.769			
	Left before medical screening exam	.040	.019	.012	2.179	.029	.004	.077	.012	.012	.012

a. Dependent Variable: Left without being seen utilizing queueing theory

Figure 12. Test of Coefficient. Linear regression Coefficients summary depicting the Beta and significance for LWBS dataset.

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.74	1.78	1.78	.005	33424
Residual	-.778	10.222	.000	.420	33424
Std. Predicted Value	-7.939	.126	.000	1.000	33424
Std. Residual	-1.852	24.339	.000	1.000	33424

a. Dependent Variable: Left without being seen utilizing queueing theory

Figure 13. Test of Residual statistics. Linear regression results depicting the residuals compared to the sample size for the LWBS dataset.

The model summary within figure 10 shows that the adjusted R^2 is .000. The analysis shown in figure 9 depicted that 0% of the variance of the dependent variable can be explained by the independent variable. While the Durbin Watson statistic at .052 depicted a positive autocorrelation between the variable and the degree of change between the variables, while the beta coefficient showed that there was a change of .04. The ANOVA table within figure 11 showed $p<.05$ at .029. Due to the findings, the null hypothesis, H_{02}- there is not statistically significant difference between capacity management utilizing Queuing Theory to reduce LWBS in the ED, can be rejected. Therefore, it can be concluded that there is a significant difference between LWBS in hospital systems that utilize queueing theory for capacity management within the ED compared to LWBS in hospital systems that do not utilize queueing theory for capacity management within the ED.

Boarding in the Emergency Department

Boarding data was analyzed to review health systems where Boarding was collected within systems that did not utilize queueing theory for capacity management compared to systems where queueing theory was utilized for capacity management within the inpatient and ED setting. A linear regression analysis was completed utilizing SPSS version 24. The dependent variable of the analysis consisted of the Boarding data from hospital systems where queueing theory was not utilized for capacity management, while the independent variable consisted of Boarding data where queueing theory was utilized within the system. An Independent Sample T-Test analysis assessed the variances of the sample, which is depicted in figure 14. Figure 15 represents the sample size analyzed for the secondary data representing LWBS.

	Boarding identifier	N	Mean	Std. Deviation	Std. Error Mean
Boarding data complete	BoaringNQ	34134	.73	2.038	.011
	BoardingQ	33661	1.63	1.487	.008

Figure 14. Group statistics and sample size for boarding. Sample size data for boarding dataset.

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Boarding data complete	Equal variances assumed	416.176	.000	-65.889	67793	.000	-.904	.014	-.931	-.877
	Equal variances not assumed			-66.029	62486.850	.000	-.904	.014	-.931	-.877

Figure 15. Independent sample T-Test boarding. Independent T-Test reviewing boarding dataset for health systems utilizing queueing theory for capacity management and health systems not using queueing theory for capacity management.

The analysis review for the Boarding Independent Sample T-Test resulted in the Levene's Test for Equality of Variances being higher than .05. It is assumed that there are not equal variances and the analysis results are depicted within the first row of figure 6. The P-value for the two-tailed significance resulted in a p-value <.05 at .000, which shows a significance difference between Boarding of health systems utilizing queueing theory for capacity management and health systems not using queueing theory for capacity management. Figure 16 represents the model summary and the adjusted R^2, while figure 17 represents the results of the ANOVA test within the linear regression analysis. The ANOVA test depicted the significance of the analysis, while figures 18 and 19 reviewed the beta coefficient and the linear regression residuals for the boarding dataset.

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.049[a]	.002	.002	1.486	.002	80.610	1	33650	.000	.012

a. Predictors: (Constant), Are admitted ED patients ever 'boarded'

b. Dependent Variable: Boarding with queueing theory

Figure 16. Model summary for linear regression. Linear regression model summary depicting the R^2 and significance for the boarding dataset.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	177.984	1	177.984	80.610	.000[b]
	Residual	74297.807	33650	2.208		
	Total	74475.791	33651			

a. Dependent Variable: Boarding with queueing theory

b. Predictors: (Constant), Are admitted ED patients ever 'boarded'

Figure 17. ANOVA test. Linear regression ANOVA summary depicting the significance for boarding dataset.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.659	.009		193.184	.000	1.642	1.676
	Are admitted ED patients ever 'boarded'	-.035	.004	-.049	-8.978	.000	-.043	-.028

a. Dependent Variable: Boarding with queueing theory

Figure 18. Test of Coefficient. Linear regression Coefficients summary depicting the Beta and significance for boarding dataset.

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.59	1.98	1.63	.073	33652
Residual	-10.623	.412	.000	1.486	33652
Std. Predicted Value	-.624	4.741	.000	1.000	33652
Std. Residual	-7.149	.277	.000	1.000	33652

a. Dependent Variable: Boarding with queueing theory

Figure 19. Test of Residual statistics. Linear regression results depicting the residuals compared to the sample size for the boarding dataset.

The model summary within figure 16 shows that the adjusted R^2 is .002. The analysis shows that 2% of the variance of the dependent variable can be explained by the independent variable. While the Durbin Watson statistic, shown in figure 16 at .012 depicted a positive autocorrelation between the variable and the degree of change between the variables, the beta coefficient in Figure 18, showed that there is a change of 1.66. The ANOVA analysis, figure 17, showed $p<.05$ at .000. Due to the findings, the null hypothesis, H_{03}- there is not a statistically significant difference between capacity management utilizing Queuing Theory to reduce in-patient boarding rates in the ED, was rejected. Therefore, it could be concluded that there was a significant difference between Boarding in hospital systems that utilize queueing theory for capacity management within the ED compared to Boarding in hospital systems that do not utilize queueing theory for capacity management within the ED.

Summary

Section 3 presented the data collection of the secondary dataset and the results for the statistical analyses conducted to answer the following research questions: RQ_1-Quantitative: What is the relationship between capacity management utilizing queueing theory and Length of Stay (LOS) in the emergency department (ED), RQ_2-Quantitative: What is the reduction in the abandonment rate or left without being seen (LWBS) rate when capacity management is utilized within the ED setting, and RQ_3-Quantitative: What is the relationship between capacity management within the ED and inpatient setting and inpatient boarding rates within the ED. An Independent T-Test with a linear regression analysis was completed on LOS, LWBS, and Boarding datasets to determine whether a relationship exists.

The first research question, RQ_1, analysis determined that the null hypothesis, H_{01}- There is not a statistically significant differences between capacity management utilizing Queuing Theory to reduce LOS in the ED, could not be rejected due to the significance of the analysis being greater than .05 at .473. The Durbin Watson statistic, however, depicted a positive autocorrelation between the variables, a statistical result of 1.554, between the variable and the degree of change between the variables. Further data analysis would be recommended to determine to true impact of LOS utilizing queueing theory within a health system compared to a health system that does not utilize queueing theory for capacity management.

The second research question, RQ_2, analysis determined that the null hypothesis, H_{02}- There is not statistically significant difference between capacity management utilizing Queuing Theory to reduce LWBS in the ED, could be rejected due to the significance of the analysis being less than .05 at .029. The Durbin Watson statistic also depicted a positive autocorrelation between the variables, a statistical result of 1.052, between the variable and the degree of change between the variables. Therefor the hypothesis can be accepted that there is there is a statistically significant difference between capacity management utilizing Queuing Theory to reduce LWBS in the ED compared to health systems that do not utilize queueing theory for capacity management.

The third research question, RQ_3, analysis determined that the null hypothesis, H_{03}- There is not a statistically significant difference between capacity management utilizing Queuing Theory to reduce in-patient boarding rates in the ED, could be rejected due to the significance of the analysis being less than .05 at .000. The Durbin Watson statistic also depicted a positive autocorrelation between the variables, a statistical result of 1.012, between the variable and the degree of change between the variables. Therefor the hypothesis can be accepted that there is there is a statistically significant difference between capacity management utilizing Queuing Theory to reduce Boarding in the ED compared to health systems that do not utilize queueing theory for capacity management.

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

Introduction

The focus of this study was the relationship between hospital systems that use queueing theory for capacity management within the ED and inpatient setting compared to hospital systems that do not use queueing theory for capacity management. I aimed to determine if there was a reduction in LOS, LWBS, and boarding rates. The quantitative nature of the study allowed for statistical analysis of the data using SPSS Version 24 to identify if a relationship existed between the variables. The study contributes to increased knowledge in the area of capacity management and processes within in the ED and inpatient setting.

ED LWBS rates are having detrimental effects on the ability for systems to service patients due to extended wait times, LOS, within the ED, and poor capacity management (Pasupathy et al., 2017). Researchers have shown that the mean wait time for abandonment is 98 minutes, and many EDs are exceeding the 98-minute mark for patients who do not need care rendered within 1 to 14 minutes (Pasupathy et al., 2017). Capacity management impacts the system as a whole, but the extent that the system is impacted has not been heavily researched and represents a need within the health care field. ED overcrowding due to patient boarding, the act of keeping patients within the ED when emergent care is not required, decreases patient quality and patient satisfaction (Chang et al., 2017). For this study, a review of secondary data allowed for the comparison of systems that use queueing theory for capacity management compared to health systems that do not use queueing theory for the purpose of reviewing LOS, LWBS, and boarding rates.

Summary of Key Findings

To answer the research questions, it was necessary to conduct a linear regression and independent sample *t*-test analyses on the variable pairings, LOS, LWBS, and boarding. LOS data analysis determined that the variances of the datasets were similar in nature, which was determined via the Levene's Test for Equality of Variances, while LWBS and boarding depicted that equal variances could not be assumed. The culmination of independent sample *t* test determined that the comparison of all three variables were significant in nature.

The review of the LOS variables depicted a positive auto-correlation during the linear regression analysis, although the significance was $p > .05$. The result was that the study's null hypothesis for LOS, there is not a statistically significant differences between capacity management using queuing theory to reduce LOS in the ED, cannot be rejected. The review of the linear regression analysis for the LWBS and boarding rate variables produced results that depicted the rejection of the null hypotheses and the acceptance of the hypotheses that there is a significant difference between LWBS and boarding rates when comparing health systems that use queueing theory for capacity management and health systems that do not use queueing theory for capacity management. In all three variable comparisons, systems that use queueing theory for capacity management had better rates compared to systems that did not use queueing theory for capacity management. Previous researchers have found statistical significance between the variables and were identified to solidify the result of the findings in the regression analysis.

Interpretation of Findings

The results of this study both confirm and extend knowledge in the field of healthcare administration and within the realm of the expansion of capacity management and the use of queueing theory to reduce LOS, LWBS, and boarding rates. Capacity management barriers contribute to longer LOS rates for patients within the ED setting due to patients encountering systematic barriers within the patient journey through the system (Armony et al., 2015). Hospital systems in the United States are facing a dilemma regarding capacity management within the ED and the inpatient care setting (Storm-Versloot et al., 2014). The result of encountering systematic barriers due to poor capacity management contributes to patients not obtaining medical care in a timely fashion, which correlates to a longer LOS, LWBS, and boarding rates (Chang et al., 2017).

Length of Stay in the Emergency Department

The independent sample t test for the LOS population sample of $N = 66{,}557$ depicted that equal variances could be assumed comparing the LOS data with the grouping variable with one group representing the population who used a system where queueing theory was implemented within the ED setting compared to the population who used a system where queueing theory was not implemented for capacity management in the ED. The Levene Test of Equality of Variances was completed to validate the aforementioned results and depicted $F > .05$. The resulting two-tailed significance depicted model significance with $p < .05$ with a linear regression analysis showing a positive auto-correlation of the samples with a Durbin Watson statistic of 1.554. The linear regression analysis further depicted that 0% of the variance of the dependent variable can be explained by the independent variable with a degree of change of .004.

Based on the linear regression analysis, the null hypothesis, that there is not a significant relationship between LOS of systems that use queueing theory for capacity management and LOS of systems that do not use queueing theory for capacity management, cannot be rejected. Researchers have linked systems that implement queueing theory for capacity management with health systems that that do not implement queueing theory for capacity management. There was improvement with LOS in respect to health systems where queueing theory was used, but the extent did not represent a strong relationship and further testing would be needed, as depicted in Wiler et al. (2013) where queueing theory decreased LOS but further research was needed to ensure validation with a larger sample size.

Left Without Being Seen in the Emergency Department

The independent sample *t* test for the LWBS population sample of $N = 67{,}558$ depicted that equal variances could be assumed comparing the LWBS data with the grouping variable, with one group representing the population that used a system where queueing theory was implemented within the ED setting compared to the population who used a system where queueing theory was not implemented for capacity management in the ED. The Levene Test of Equality of Variances was completed to validate the aforementioned results and depicted $F > .05$. The resulting two-tailed significance depicted model significance with $p < .05$, with a linear regression analysis showing a positive auto-correlation of the samples with a Durbin Watson statistic of .052. The linear regression analysis further depicted that 0% of the variance of the dependent variable can be explained by the independent variable with a degree of change of .040.

Based on the linear regression analysis, the null hypothesis, that there is not a significant relationship between LWBS of systems that use queueing theory for capacity management and LWBS of systems that do not use queueing theory for capacity management, can be rejected. Long wait times prior to being placed into a room within the ED and inpatient setting is related to lower patient satisfaction with the perceived quality of care in which the patient receives and higher LWBS rates (Storm-Versloot et al., 2014). Researchers have shown that the mean wait time for abandonment is 98 minutes, and many EDs are exceeding the 98-minute mark for patients who do not need care rendered within 1 to 14 minutes, with many patients leaving without being seen (Pasupathy et al., 2017). The reduction of wait times within the ED setting may be a contributing factor in lowering the rate in which patients leave the ED setting without care rendered. Lower LWBS rates ensure that patients are receiving the required level of care with possible outcome of increased patient satisfaction.

Boarding in the Emergency Department

The independent sample *t* test for the LWBS population sample of *N* = 67,795 depicted that equal variances could be assumed comparing the LWBS data with the grouping variable, with one group representing the population who used a system where queueing theory was implemented within the ED setting compared to the population who used a system where queueing theory was not implemented for capacity management in the ED. The Levene Test of Equality of Variances was completed to validate the aforementioned results and depicted $F > .05$. The resulting two-tailed significance depicted model significance with $p < .05$, with a linear regression analysis showing a positive auto-correlation of the samples with a Durbin Watson statistic of .012. The linear regression analysis further depicted that 2% of the variance of the dependent variable can be explained by the independent variable with a degree of change of 1.66.

Based on the linear regression analysis, the null hypothesis, that there is not a significant relationship between LWBS of systems that use queueing theory for capacity management and LWBS of systems that do not use queueing theory for capacity management, can be rejected. Researchers have shown that overcrowding by patients improperly using the ED for health care needs, paired with patients being moved to the inpatient care setting due to improper acuity and triage evaluations, has led to a higher mortality rate and patient satisfaction within hospital systems as well as higher boarding rates within the ED (Chang et al., 2017). The results are consistent to research in the health care field that relayed the importance of administrative involvement across the continuum of care and the need for standardization of capacity management processes across the hospital system as a whole and not solely a departmental level.

Analyzing and Interpreting the Findings in Theory Context

The results of the study support the theory in context that queue lines or processes of throughput have fluid limits and can be predicted through the use of mathematical equations, such as Queueing theory (Heyde, 2001). Application of Erlang's Queuing Theory offers support of the utilization of Queueing theory in the hospital system setting in order to improve organizational performance and the increase in health care and patient demand (Bittencourt, Verter, & Yalovsky, 2018). A health system has control of the efficiency of the pathways that a patient may travel through, and the utilization of queueing theory allows for the barriers to efficiency to be noted and adapted. In a health system, inefficient practices lead to higher LOS, LWBS rates, and boarding rates (Chang et al., 2017). The application of queueing theory maximizes the efficiency of the patient throughput and the processes by which the health system operates in respect to capacity management. The variables that the analyses have proven to be statistically significant align directly with the constructs.

The linear regression analysis completed on the variables resulted in statistically significant findings regarding the relationship between health systems that utilize queueing theory for capacity management and health systems that do not utilize queueing theory for capacity management. The Independent Sample T-Test displayed variances that were similar in nature with systems utilizing queueing theory depicting a decrease in the rate of LOS, LWBS, and boarding. The patient represents the parts moving through the system with the completion of the process at patient discharge from the system. Barriers within the process, such as in departments like the ED or inpatient setting, can cause systematic disruption with the patient's journey through the system, increasing factors such as LOS, LWBS, and boarding rates (Chang et al., 2017). The systematic disruption has a trickle-down effect on clinical outcomes and hospital reimbursement, and the impact of capacity management within the ED and inpatient setting on system outcomes is not widely reviewed and analyzed (Chang et al., 2017).

Limitations of the Study

A limitation that remained a constant within this study was the use of archival data from a previous study of the utilization of queueing theory in a health system (Wiler et al., 2013), as well as the NEDS and NHAMC national surveys. Selection, quality, included variables, and the method of data collection were not under the control of this study, and validation was not possible. The limitation was mitigated through the combination of datasets under the parameters of the study and the data points outside of the parameters of this study were excluded.

An additional limitation is that the data for the national surveys is subject to the data collected and dispersed by the individual health systems. The standardization of Electronic Medical Records could not be confirmed across the systems that participated within the secondary data collection process. Brundin-Mather et al. (2018) depict that manual collection for secondary data collection for health outcomes pose a higher risk of discrepancies due to human error than utilizing differing EMR technologies. It is an assumption of this study that health systems had varied uses of EMR technology and capabilities during the data collection process. The limitation was mitigated by the parameters set forth by the secondary data collection process and studies. Specifically, collection at standardized points of care within the patient's care journey, such as the measurement and definition of LOS, LWBS, and boarding.

A limitation that cannot be mitigated is the inclusion of rural health system data within the secondary data sets. Due to anonymous data, specific hospital systems utilized for non-queueing theory capacity management could not be determined. Therefore, the inclusion of rural health system data sets could create outliers within the data analysis. Data collection for health systems utilizing queueing theory for capacity management consisted of urban systems only. According to Matthews et al. (2017), access to care behaviors may vary between a population that is designated as rural in nature compared to a population that self-describes as living within an urban area and accesses care within the urban setting.

Recommendations

In this research study, the significance between hospital systems that utilize queueing theory for capacity management within the emergency department (ED) compared to health systems that do not utilize queueing theory for capacity management within the ED was analyzed. The goal was to highlight the variables of length of stay, left without being seen, and boarding rates. Data was available via the United States Department of Health and Human Services (DHS), Centers for Disease Control and Prevention, and the National Center for Health Statistics within the NHAMCS for systems who did not utilize queueing theory for capacity management, as well as the Agency for Healthcare Research and Quality (AHRQ) utilizing the NEDS survey ("NHAMCS, 2008", 2011). Although data was available for health systems utilizing queueing theory for capacity management, a greater sampling and review of literature would be recommended to further close the knowledge gap.

The results and limitations of the study make it necessary to highlight possible recommendations for future research regarding the use of queueing theory for capacity management within health systems. One recommendation is to replicate this study using a more diverse population sample, including health systems with rural hospitals and emergency departments. Matthews et al. (2017) defines the rural health system, even if an affiliate of an urban flagship health system, to define and respond to access to care differently due to the differing needs of the rural population. To minimize outliers within the dataset for health systems utilizing queueing theory for capacity management and health systems not utilizing queueing theory for capacity management, it is recommended that rural systems be included and reviewed for both factors.

A second recommendations would be to emulate the study with health systems that utilize the same EMR to ensure that the timestamps for the collection process for the variables of LOS, LWBS, and boarding are done in the same manner to help reduce the possibility of error within the collection process. Although EMR data collection is the preferred method for the reduction of collection related errors, the use of one EMR would ensure that the coding of the EMR and idiosyncrasies in the data collection process are limited (Brundin-Mather et al., 2018).

A third recommendation would be to complete the study 12 months post implementation of the systems implementing queueing theory to ensure the standardization and adoption of processes throughout the system. Unstructured data collection, communication and processes within the health system, can have an adverse reaction on the data collection completed by an EMR and defined within an EMR, such has LOS, LWBS, and boarding (Polnaszek et al., 2016). Ensuring that unstructured data is defined, standardized, and tested will help ensure that the data collected within the EMR has limited external factors which may cause errors with the data collection.

Quantitative research method was used in this study because of the use of secondary data. Quantitative data collection was utilized reviewing the key outcome areas and the response time for the data entered within the health system's EMR with the purpose of creating a mechanism for efficient work flow and data entry processes to reduce the minutes a clinician spends on non-patient-oriented tasks, thus reducing LOS, LWBS and boarding rates.

However, improving upon the limitations of this study would probably be better suited using a qualitative or mixed method approach with the use of primary data, specifically reviewing the patient perspective and how the patient perspective may contribute to the patient decision-making process. Primary data Researchers would be able hear from patients directly and would be better able to eliminate biases and validate the data used in the study.

The final recommendation of this study would be for greater partnerships between government agencies and health systems to work together to address the issue of emergency department capacity management constraints. Specifically, due to the capacity management constraints hindering the ability for patients to access the appropriate level of care in an appropriate amount of time. Standardizing acceptable benchmarks for LOS, LWBS, and boarding rates to fiscal means and reimbursements would better motivate health systems to ensure that processes and tools are utilized effectively and efficiently within the health systems to minimize factors that could be detrimental to population health. Although initiatives exist, the emphasis is limited, resulting in a significant gap in research.

Implications for Professional Practice

Identifying tools and effective practices to reduce length of stay, left without being seen, and boarding rates within the emergency department setting presents implications for both professional practice and social change. For professional practice, the findings of this study might help health systems look outside of traditional capacity management practices in order to assist in capacity management constraints, such as queueing theory which was primarily used in the manufacturing setting. An additional insight that may be added to the professional practice is the promotion of a systems approach within a health system that reflects a system of interconnected departments rather than separately regulated, independent departments within the system. The use of a systems approach may assist in the fluidity of the patient journey through the health system regardless of the patient's individual medical needs. Creating a more fluid patient journey, and better access to the correct level of care in a times fashion, may better assist physicians and health systems in delivering effective and efficient care with the best possible outcomes.

Implications for Positive Social Change

Understanding the systematic barriers within health systems that may hinder population health and access to emergent care is critical. Having that understanding is crucial for a health to ensure that the population that the health system serves obtains the right care at the right time. Addressing these barriers has the potential to assist in better outcomes for patients, as well as quicker and more effective health care delivery. Fluidity with the patient care journey within the system may create less stress for the patient, as well as for the providers caring for the patients due to more effective and efficient practices. Reducing length of stay, left without being seen, and boarding rates could create better outcomes for the health system, as well as the population being served by the health system.

The findings of this study may also assist collaboration amongst health systems and government agencies with an emphasis on population health and access to care. The reduction of left without being seen rates ensure that patients are obtaining care that is needed, while a reduction in length of stay and boarding rates ensures that the care is rendered in the appropriate timeframe. queueing theory is adaptable for the varying and individualized needs of health systems, which allows for cross-system expansion. The findings within this study has the potential to unlock the access to a more fluid, effective, and efficient patient journey. A journey where the patient's medical needs are met in the quickest and most effective manner.

Conclusion

In summary, the focus of this study was to research the relationship between health systems that utilize queueing theory for capacity management and health systems that do not utilize queueing theory for capacity management. The variables analyzed were length of stay (LOS), left without being seen (LWBS), and boarding rates. A power analysis determined that the sample size for the populations analyzed were sufficient to progress to a linear regression analysis with an Independent Sample T-Test analysis. The results of the analysis and Durbin Watson statistic depicted a positive auto-correlation between all three variables assessed, while LWBS and boarding rates showed a significant decrease within health systems utilizing queueing theory for capacity management.

The results of the study confirm and extend knowledge in the healthcare administration discipline that effective and efficient capacity management techniques can reduce a patient's LOS, while the health system can see a reduction in LWBS and boarding rates. The outcomes of the statistical analyses align the study with the contextual framework of the study and the use of queueing theory within the health care setting. Further research and advancement of knowledge in the use of queueing theory would be beneficial to the field of health care.

The findings of this study could help create positive social change by equipping government agencies and health care providers to understand the impact of LOS, LWBS, and boarding in the emergent care setting on the patient experience and the impact on patient health outcomes. This information might be instrumental in creating healthcare policies and the improvement of the delivery of healthcare services across the patient populous, while also promoting better patient health outcomes throughout the entirety of the patient journey within the health system. The findings of this study may help cultivate greater access to care for patients and greater population health outcomes.

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