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Queueing Variables and Leave-Without-Treatment Rates in the Emergency Room

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Abstract

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MM, Cambridge College, 2008

BS, Elms College, 2000

Proposal Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Business Administration

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Abstract

Hospitals stand to lose millions of dollars in revenue due to patients who leave without treatment (LWT). Grounded in queueing theory, the purpose of this correlational study was to examine the relationship between daily arrivals, daily staffing, triage time, emergency severity index (ESI), rooming time, door-to-provider time (DTPT), and LWT rates. The target population comprised patients who visited a Connecticut emergency room between October 1, 2017, and May 31, 2018. Archival records ($N = 154$) were analyzed using multiple linear regression analysis. The results of the multiple linear regression were statistically significant, with $F(9,144) = 2902.49$, $p < .001$, and $R^2 = 0.99$, indicating 99% of the variation in LWT was accounted for by the predictor variables. ESI levels were the only variables making a significant contribution to the regression model. The implications for positive social change include the potential for patients to experience increased satisfaction due to the high quality of care and overall improvement in public health outcomes. Hospital leaders might use the information from this study to mitigate LWT rates and modify or manage staffing levels, time that patients must wait for triage, room placement, and DTPT to decrease the rate of LWT in the emergency room.

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Dedication

I dedicate this study to my God who promises in His Word…but they that wait upon the LORD shall renew their strength; they shall mount up with wings as eagles; they shall run, and not be weary; they shall walk, and not faint (Isaiah 40:31). God has sustained and upheld me through this perilous and toilsome journey and given me a loving husband, wonderful parents, and caring friends for support.

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Thank you to my parents Jay and Beverly Wordsworth for believing in me and for all your spiritual and emotional guidance to get me to this point in my life. Thank you to my husband, Michael Gibbs, for staying by my side, even when I was not physically or emotionally available to be a good wife. I also thank my friends, for their encouragement and love despite my absence for the last five years; I was always longing to spend more time with them. I express my gratitude to Dr. Reginald Taylor, my Chair because the completion of this project would not have been possible without the many hours and hard work he contributed on my behalf. I also appreciate the feedback and time that my second committee member, Dr. Kelly Chermack, has taken to hear my defenses and review my work.

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Section 1: Foundation of the Study

Background of the Problem

From 1994 to 2014, emergency room (ER) visits in the United States increased from 90.5 to 136.3 million (American Hospital Association [AHA], 2016). At the same time, the AHA (2016) reported that the number of ERs to meet this demand dropped from 4,960 in 1994 to 4,408 in 2014. The increase in visits and a decrease in service capacity has resulted in overcrowding in U. S. hospitals.

ER overcrowding is a worldwide crisis as well (Khalifa & Zabani, 2016). Congestion leads to long wait times for patients, and some eventually grow tired of waiting and leave without treatment (LWT) from a medical provider. The LWT problem concerns hospital leaders owing to lost revenue and lower patient satisfaction scores. According to Lucas, Batt, and Soremekun (2014), a linear relationship exists between the time a customer spends in the queue and the probability that he or she will abandon the queue before service. I have described the background regarding the LWT phenomenon and will now focus on the problem statement for my study.

Problem Statement

Patients who visit hospital ERs and LWT negatively influence hospital revenue (Lucas et al., 2014). The average hospital loses approximately $1,233 for every LWT in the ER, based on the median charge for the 10 most commonly treated outpatient conditions (Caldwell, Srebotnjak, Wang, and Hsia, 2013). The general business problem is that hospitals are losing potential reimbursement when patients LWT. The specific business problem is that some hospital leaders do not know the relationship between daily arrivals, daily staffing, triage time, emergency severity index (ESI), rooming time, door-to-provider time (DTPT), and LWT rates in the ER.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between the predictor variables of daily arrivals, daily staffing, triage time, ESI, rooming time, DTPT, and the dependent variable LWT. The targeted population included patients of all ages who visited the participating ER between October 1, 2017, and May 31, 2018. Implications for positive social change resulting from this study include the potential for patients to experience increased satisfaction due to the high quality of care and overall better public health outcomes. Hospital leaders may use the information from this study to project the potential for LWT and modify or manage the staffing levels, and times that patients must wait for triage, room placement, and DTPT to decrease the rate of LWT in the ER.

Nature of the Study

My research question and purpose made this study inherently quantitative. Because the research question pertains to relationships between variables, there was no role for qualitative inquiry. A researcher may choose to use qualitative, quantitative, or mixed-methodology to conduct a study (Gibson, 2017). Qualitative researchers seek to answer questions by collecting individual or group data about the lived experiences of people and formulating conclusions inductively (Moon et al., 2013).

Conversely, quantitative researchers use a deductive approach, starting with a generalized hypothesis and then using numerical data for support (Moon et al., 2013).

The quantitative methodology was the most appropriate choice for my study because I only collected statistical data. A researcher using mixed methodology includes both qualitative and quantitative elements to answer the research question (Gibson, 2016; Spillman, 2014). My study did not consist of any qualitative data, so the mixed methodology was not an appropriate choice.

Quantitative research designs include, but are not limited to, correlation designs, experimental designs, and causal-comparative designs (Bleske-Rechek, Morrison, & Heidtke, 2015; Hudson & Llosa, 2015). According to Hudson and Llosa (2015), researchers choose correlation to find relationships between variables, whereas the desired outcome of experimental design is to explain causality between variables. A researcher uses causal-comparative design to compare two or more groups for the same outcome variable (Doody & Bailey, 2016). The purpose of this study was to find relationships between the predictor variables and the dependent variable. Uncovering the exact causes of LWT was beyond the scope of this study, and there were no groups for comparison. Therefore, the correlation design was the most suitable choice to answer my research question.

Research Question

What is the relationship between daily arrivals, daily staffing, triage time, ESI, rooming time, DTPT, and LWT rates in the ER?

Hypotheses

H_0: There is no relationship between daily arrivals, daily staffing, triage time, ESI, rooming time, DTPT, and LWT rates in the ER.

H_1: There is a relationship between daily arrivals, daily staffing, triage time, ESI, rooming time, DTPT, and LWT rates in the ER.

Theoretical Framework

According to Bhat (2015) and Roy (2016), A. K. Erlang is the father of queueing theory (QT) because he had many essays related to QT concepts that were published by Copenhagen Telephone Company to resolve problems of congested telephone traffic and to improve operations in telecommunications. All of Erlang's original works were published in Danish and later in French (for a chronological list of publications, see Appendix A). However, the only publications translated into English are found in *The Life and Works of A. K. Erlang* (Brockmeyer, Halström, & Jensen, 1948). Erlang's work fell into several categories including probability theory, stochastic processes, theoretical physics, and population statistics (Brockmeyer et al., 1948). QT later became a branch of operations research using a mathematical approach to study congestion and delays of waiting in line (Bhat, 2015). Although QT has origins in operations research, the theory helps users to make wise business decisions regarding efficient and cost-effective workflow in the ER (Hu, Barnes & Golden, 2018). According to Bhat, QT allows researchers to examine every aspect of waiting in line for service, including the arrival process, service process, number of servers, number of stops within the system, and the number of customers. Furthermore, QT allows researchers to calculate performance metrics such as wait time, average queue length, and the proportion of customers that the organization has to turn away from service (Gupta, 2013; Hu et al., 2018).

Key variables of QT relating to the ER environment include daily patient arrivals, regular direct care staff, waiting times for service, and the priority in which patients receive assistance (Vass & Szabo, 2015). The hypotheses for this study indicated that the following variables would or would not significantly predict LWT rates in the ER: Daily arrivals, daily staffing, triage time, ESI, rooming time, and DTPT. The tenability of these hypotheses was based upon extant literature where researchers found significant relationships between queueing variables and ER outcomes such as LWT (see Alavi-Moghaddam et al., 2012; Armony et al., 2015; Casalino et al., 2016; Handel et al., 2014; Pines, Decker, & Hu, 2012; Tropea et al., 2012; Vass & Szabo, 2015).

Operational Definitions

Daily patient arrivals: The daily patient arrivals are an indication of the total number of patients that sign up for service in the ER on a regular basis (Krall, Cornelius, & Addison, 2014).

Daily staffing: Daily staffing refers to the number of direct care staff available to provide service to customers during a 24 hour time frame (Armony et al., 2015).

Emergency severity index (ESI): The ESI is a triage tool the nurse uses to anticipate the number of diagnostic tests and procedures the patient will utilize and to assign an acuity level (Gilboy, Tanabe, Travers, & Rosenau, 2012). According to Gilboy et al. (2012), ESI levels are as follows: ESI1 (resuscitation), ESI2 (emergent), ESI3 (urgent), ESI4 (less urgent), and ESI5 (nonurgent).

Kendall's notation: A taxonomy that represents the various elements of a queueing model (Bhat, 2015).

Left without treatment or leave without treatment (LWT): LWT refers to the total number of patients who depart or departed from the ER before an examination by a provider which includes a physician, advanced practice registered nurse (APRN), or physician's assistant (Wiler et al., 2015).

Door-to-provider time (DTPT): The DTPT is the time it takes for the provider to initiate the medical screening evaluation after the staff member places the patient in a room (Krall et al., 2014).

Queueing discipline: The queueing discipline is synonymous with the order in which customers receive service (or the priority) also known as a class in queueing theory (Bhat, 2015).

Queueing network: The queueing network is the flow of patients through a hospital system with an entrance and exit point, where medical staff work in single or multiserver nodes (Bhattacharjee & Ray, 2014).

Rooming time: The rooming time is the amount of time that passes from when the patient first signs into the ER until a staff member places the patient in a room or treatment area to wait for the medical screening evaluation (Pielsticker, Whelan, Arthur, & Thomas, 2015).

Triage time: The triage time is the amount of time that passes between ER registration and the triage process, where the nurse assigns the patient an acuity level (Storm-Versloot, Vermeulen, van Lammeren, Luitse, & Goslings, 2014).

Assumptions, Limitations, and Delimitations

Assumptions, limitations, and delimitations are critical restrictions that a researcher must reveal regarding the availability of resources or other issues or shortcomings that arise throughout the study (Simon & Goes, 2013). In the next section, I will describe some assumptions, limitations, and delimitations for my research.

Assumptions

Assumptions are information the researcher takes for granted, or assumes as truth, even though no concrete proof validates the information (Simon & Goes, 2013). I was assuming that the hospital staff entered the information correctly into the database ensuring the accuracy of the archival data for this study. I also assumed that the sample I chose for my research would represent the ER population so that conclusions from my analysis would apply to other ERs with similar characteristics.

Limitations

Limitations refer to potential weaknesses of the study or an uncontrollable threat to the internal validity of a study (LoBiondo-Wood & Haber, 2013). One limitation is that correlational research design can only help the researcher to predict a relationship between variables, not determine a causal relationship between variables (Simon & Goes, 2013). Another limitation is that archival data collection comprises the secondary analysis of existing data (Schulz, Hoffman, & Reiter-Palmon, 2005; Cheng & Phillips, 2014). The limitation of the secondary analysis is that the researchers who are analyzing the data are not the same individuals involved in the data collection process (Cheng & Phillips, 2014). According to Cheng & Phillips (2014), this is problematic because the researcher is not aware of glitches in the data collection process which may end up compromising the validity of the study results.

Delimitations

Delimitations refer to the bounds or scope of the study within the researcher's control such as the choice of a problem to study (Simon & Goes, 2013). Many internal hospital problems and external factors may influence LWT. However, to narrow the scope of this study, I only included variables relating to QT. The Health Insurance Portability and Accountability Act (HIPAA) places limits on the researchers' abilities to directly access and contact patients (U.S. Department of Health & Human Services, 2013). To comply with HIPAA, the dataset for this study did not include other variables that may impact LWT, such as zip codes, race, ethnicity or specific age groups of the study population. This study consisted of archival data records from only one community ER, located in Connecticut, so results could differ depending on the location of the ER (e.g., environment, state, nation). The population for this study includes patients of all ages and ESI2, ESI3, ESI4, and ESI5. I did not include ESI1 patients in this study because these patients require resuscitation or life-saving interventions and cannot LWT.

Significance of the Study

According to Anderson, Pimentel, Golden, Wasil, and Hirshon (2015), hospital leaders should understand the variables related to ER operations and LWT to improve the efficiency and effectiveness of care provision. ER staff delivers an essential public service by providing care 24 hours a day and 365 days a year, without any attention to patients' socioeconomic status (Gul & Guneri, 2015; Verelst, Wouters, Gillet, & van den

Berghe, 2015). In ERs, a large population of potential patients exists, and the number of patients receiving or awaiting service does not influence the arrival rate (Hall, Belson, Murali, & Dessouky, 2013). QT has had applications in other industries besides health care, but there exists a gap in QT literature regarding the ER. Yiadom et al. (2015) held a consensus conference to advance research in ER operations to develop a framework for the understudied area of operations research in the ER. The key initiatives for improvement in ER operations research were: 1) the development of standard measures for ER patient care processes; 2) best practice compliance and process efficiency with attention on patient outcomes; 3) studies in multiple ERs to allow for more generalizable knowledge; 4) mixed-methods studies for further comprehension of the social community and human behaviors that affect ER operations; 5) the development of robust research registries for better evidence-based research; 6) prioritization of crucial research questions with the input of patients, providers, payers, and other stakeholders; 7) obtaining more consistent definitions for ER components including fast tracks, waiting rooms, and subunits such as radiology and laboratory; and 8) dissemination of knowledge to all disciplines in emergency medicine, public health, operations research, general medicine, and other publications (Yiadom et al., 2015). The significance of filling a research gap in the area of ER research is the awareness it will provide leaders, so every patient can equally experience access to care and emergency resources. Furthermore, hospital leaders can apply the information to reduce LWT, which is a significant quality indicator. Ideally, no patient would ever leave without service, and the hospital would receive full payment for every resource. Patient satisfaction is an essential aspect of health care, and total reimbursement for care depends on high Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) scores, a national satisfaction survey (Centers for Medicare & Medicaid Services [CMS], 2015).

At the time of this study, the HCAHPS scores affected only inpatient reimbursement, but an Emergency Department Patient Experiences with Care (EDPEC) survey is in the pilot phase (CMS, 2016). According to CMS (2018), the surveys will question patients about their experiences upon arrival to the ER, their care in the ER, and their experiences after they are admitted to the hospital or discharged from the ER. The CMS website (2018) authors advise readers that the patient experience data will allow for comparison of ER's nationally to assist patients with effective communication and coordination of ER care. The EDPEC survey is still in the development phase (CMS, 2018).

When patients LWT, their expectations are unmet and, due to low satisfaction, they may not recommend the hospital to people they know (Ameh, Sabo, & Oyefabi, 2013). A high LWT rate indicates many poor patient experiences and can contribute to a poor public image for a hospital (Anderson et al., 2016). Cochrane et al. (2015) found hospitals with higher patient satisfaction scores also had a shorter average DTPT and fewer LWT. Access block refers to the patient's inability to gain entry to the appropriate hospital bed because of overcrowding and throughput issues (Crawford et al., 2014). Hospital leaders may be able to identify areas of potential access block and act to reduce the problem of ER congestion (Ajmi et al., 2015). According to Abo-Hamad and Arisha (2013), understanding all aspects of patient flow through the ER is necessary for hospital leaders to make effective business decisions and provide solutions for ER process improvement. It is crucial for hospital leaders to know what factors relate to queue formation and waiting because of the many adverse consequences of waiting for care (e.g., frustration for patients and family, patient health deterioration, possible escalation of a psychiatric emergency, and increased potential for mortality).

Implications for Social Change

Patients who LWT are a high-risk group for medical and legal reasons, and operational outcomes, such as patient satisfaction (Pielsticker et al., 2015). If hospital leaders understand factors relating to LWT, they can mitigate the effects of overcrowding and long waits in the ER. It is unrealistic to expect a zero rate for LWT because some patient complaints safely resolve after arrival to the ER without any medical intervention (Vierheller, 2013). Nevertheless, hospital leaders should attempt to achieve or beat the national benchmark by striving to keep the LWT rate below 2% (Handel et al., 2014). Meeting the benchmark for LWT rates is an opportunity for hospital leaders to increase patient satisfaction and to allow their staff to provide quality care.

A Review of the Professional and Academic Literature

Onwuegbuzie and Frels (2016) defined a comprehensive literature review as a multi-modal approach a researcher uses to inform his or her knowledge base and to confirm, modify, or expand on a theory. I found the majority of journal articles for this literature review in online databases, predominately Science Direct, which only posts peer-reviewed material. The other databases that I used were: Academic Search Complete, Business Source Complete, CINAHL Plus with Full Text, Directory of Open

Access Journals (DOAJ), Dissertations and Theses @ Walden University, IEEE Xplore Digital Library, Medline with Full Text, ProQuest Central, SAGE Journals, Taylor and Francis Online, Thoreau Multi-Database Search, and Ulrich's Periodicals Directory. I verified 85% of the total sources were peer-reviewed on Ulrich's or visited the journal home pages to confirm the refereed status of the literature. The other 15% were books and government websites. I focused on peer-reviewed studies less than 5 years old at the time of conducting my doctoral research. Out of 144 resources, 20 were published before 2013. Therefore, 13% of resources do not fall within the 5-year requirement, and 87% of the resources do (meeting the 85% rule). I only cited earlier publications for the necessity of introducing work by pioneers in the field of queueing theory or when no current research was available on the ER variables. The key search terms for the literature review were combinations of the following words: queues, abandonment, reneging, call centers, left without being seen (LWBS), left without treatment (LWT), emergency department, emergency room, queueing theory, and also an alternative spelling queuing theory.

The first portion of the literature review contains an analysis and synthesis of literature related to queueing theory research. More specifically, there is a review of the queueing theory research as it applies to call centers to give the reader a foundation on the queueing variables. I have organized the variables sequentially to follow the natural progression of events in a call center or ER. The queueing variable names for call centers are different from the ER owing to the context of the setting. For example, where the dependent variable is LWT in the ER, the same queueing variable is caller abandonment in a call center. Predictor variables will have different names as well. When comparing the ER predictor variables to call center variables, note that servers correspond to agents. Patient arrivals equate to call arrivals. Triage time, rooming time, and DTPT compare to service rates. Finally, the ESI level corresponds to the priority of service.

After the discussion of queueing variables as they relate to call centers, I will continue the literature review with an overview of the research on the queueing variables for my study. First, I will present studies regarding the dependent variable LWT. Next, I will discuss the predictor variables in this sequence: Patient arrivals, staffing, triage time, ESI, rooming time, and DTPT. There is very little research available using QT to improve operational outcomes in the ER. Researchers have used other models, besides QT, to frame problems in the ER, without offering any practical solutions. For example, Asplin et al. (2003) presented a conceptual model dividing the ER into three interdependent components: Input, throughput, and output. Despite the goal of Asplin et al. (2003) to provide a practical framework to organize research, policy, and operations agenda, the problem of ER crowding is not alleviated 15 years later. According to Khalifa and Zabani (2016), research and application of healthcare analytics are no longer merely descriptive, but moving into sophisticated diagnostic, predictive, and prescriptive approaches. I hope to fill a gap in ER operations research by showing hospital leaders how to transfer queueing principles from the call center industry to healthcare to reduce LWT effectively.

QT

Batt and Terwiesch (2015) studied the behavioral attributes of waiting, the adverse impact it has on customers, and the loss of revenue that businesses incurred from making customers wait for service. When designing a queueing system, Armony et al. (2015) studied the psychology of waiting and considered how people perceived their waits. Queueing scientists are concerned with congestion, waiting and blocking, and limitations in resources (He, Liu, & Whitt, 2016). According to Bhat (2015), before the introduction of call waiting buffers, telephone systems operated as loss systems and traffic engineers used Erlang's loss formula, or Erlang's first formula to calculate the number of customers who could not enter the system. An Erlang is a measurement of the offered load (ratio of the arrival rate to the service rate) in teletraffic (Bhat, 2015). Barrer (1957) later referred to impatient customers as those who would only wait a fixed amount of time, after which the business would lose the customer. Barrer's solution had minimal applications with one primary parameter of interest (ratio of the average departure rate to the average arrival rate) and reference to only single server cases where customers arrived on a first come first serve (FCFS) basis. Developers of other formulas and methods considered the queueing system in a steady state only and did not take into account arrival rates that varied with time. Little's law ($L = \lambda W$) is the most basic queueing model but assumes all arrivals are Poisson distribution and service times are exponential (Little & Graves, 2008). In other words, the long-term average (L) equals the average effective arrival rate (λ) multiplied by the average wait time in the system (W). According to Little and Graves (2008), a Poisson distribution in statistics shows the likely number of times that an event will occur within a specific interval of time. It is used for independent events which occur at a constant rate within a given interval of time. The Poisson distribution is a discrete function, meaning that the event can only be measured as occurring or not occurring where the service rate is constant, and two events cannot occur at the same time. Fractional occurrences of the event are not a part of the model, so only whole numbers can fit into the model. Considering that the rate at which events occur is never constant in a call center or ER, a discrete frequency model is not helpful for predicting ER arrivals or call arrivals. Liu and Whitt (2017) expanded on Little's law and Poisson models by studying call systems with time-varying arrivals, multiple servers, and more than one service phase.

Abandonment in call centers. Mandelbaum and Zeltyn (2013) argued that queueing models including abandonment or impatience were more robust and numerically stable than models that ignored abandonment. Erlang models can only represent simple single skill inbound call centers where all calls are similar, and agents handle calls in the same manner (Akşin, Ata, Emadi, & Su, 2013). Jouini, Koole, and Roubos (2013) and Robbins (2016) studied the assumptions of the Erlang C model, also known as Erlangs's delay formula or Erlang's second formula. Jouini et al. (2013) found the Erlang A model was more accurate than the Erlang C (the most common model) because it assigned abandonment times. However, Robbins (2016) did not find the Erlang A model reliable because the call center performance was better than what the model predicted. When the manager staffed based on the model, there was a gross underestimation of production resulting in lost revenue from overstaffing and idle time of agents. Ding, Remerova, van der Mei, and Zwart (2015) found the Erlang A model was numerically valid for a busy call center with redials and reconnects. Therefore, Erlang A was more useful in practice, allowing successful calculation of service levels and abandonment probabilities as long as the total arrival rates were available as inputs.

Conley (2013) used Kaplan-Meier survival analysis to obtain a full picture of caller impatience by analyzing, not only the calls the agents answered, but also caller abandonment. According to Conley (2013), Kaplan-Meier was a method of analysis used to determine the length of survival time in medical studies, where mortality was the event of interest. Kaplan-Meier allows for the use of censored data for the event of interest. Call abandonment was considered right-censored when the agents answered the calls before the caller reached their maximum level of patience and abandoned. Therefore, it was not known how long the callers would have waited, but there was information on how long they did wait, which was included in the study. Conley (2013) found that including the wait times for both the abandoned and the answered calls gave a complete picture of caller patience.

Conley and Grabau (2013) conducted four separate experiments with a concentration on increasing the number and use of designated-hybrid or hybrid resources. The four experiments were as follows: 1) elimination of all types of hybrids; 2) moving all designated-hybrids to hybrids; 3) moving all resources to designated-hybrids for their respective channel; 4) moving all resources to hybrids. They compared the as-is results from the validated model to each to-be experiment to determine impact. Conley and

Grabeau found across all experiments, hybrid resources, a combination of billing and claims agents, was best for lowering caller abandonment.

Akşin, Ata, Emadi, and Su (2013) modeled endogenous behavior such as rewards and costs of waiting including the decision making process of callers to abandon a call or continue to wait. Akşin, Ata, et al. modeled caller utility as a function of the cost of waiting and reward for service. They used a random-coefficients model to capture the heterogeneity of the callers and estimate the cost and reward parameters of the callers using the data from individual calls made to an Israeli call center. They also conducted a series of what-if analyses to test the effects of changes in service discipline on resulting waiting times and abandonment rates. Their analysis revealed that modeling endogenous caller behavior was significant when there was a change in service discipline. However, using a model with an exogenously specified abandonment distribution was misleading. Akşin, Ata, et al. (2013) formulated structural estimation problems to find callers' patience time distributions in comparison to exogenous data. For the structural estimation, Akşin, Ata et al. needed data on the state of the call center and data regarding caller choices. Under a static policy, they found a significant difference between the exogenous and the endogenous models, illustrating the importance of modeling the caller as a strategic decision maker.

Number of agents. The varying demand for service in call centers is a constant challenge to managers when trying to schedule the number of agents (Zhang van Leeuwaarden, & Zwart, 2012). Chromy and Kavacky (2016) estimated the optimal number of agents by placing modified parameters into the Erlang C equation. According to Chromy and Kavacky, the most critical part of the call centers were the agents and having accurate measurements of activities during work. They included a parameter for the number of calls the agent handled during peak hours. They also took into account other factors, such as time for breaks and time for other activities besides serving the customer, such as administrative tasks.

Flexible architecture, cross-trained servers, and pooling of resources may lead to better performance in call centers operating under demand uncertainty (Akşin, Cakan, Karaesmen, & Ormeci, 2015; Legros, Jouini, & Dallery, 2015). Akşin, Cakan et al. (2015) found there were systems improvements when managers used resource flexibility and cross-trained agents, otherwise known as skills-based routing. Legros et al. (2015) stated that a flexible call center design with single pooling decreased the blocking effect of long service times. Qin, Nembhard, and Barnes (2015) suggested queueing models or the Markov decision process as methods for implementation of teamwork or floating classes of workers to areas of greatest need. Qin et al. (2015) attempted to match staffing with demand using the Markov process as a tool to model systems and queueing theory for evaluating performance, and for improving system operation while optimizing its performance. Kim, Klimenok, and Dudin (2016) also used Markov process to provide an accurate representation of system performance measures and performed numerical experiments to confirm that the call center profited when there was an adequate number of agents. The problem with calculating staffing needs in steady-state conditions is it does not take into account the randomness which occurs with time-varying arrivals. In a deterministic queueing model, a number of arrivals and the availability of resources are known (Fores & Krarup, 2013). However, in dynamic queueing networks, such as ERs and call centers, changes in demand and resources over time make it difficult for managers to determine staffing needs (Kim & Whitt, 2014). Bhat (2015) defined a stochastic process as a sequence of random variables that are indexed by a parameter such as time. Stochastic programming is an approach that takes into account the indefinite number of call arrivals in workforce scheduling (Excoffier, Gicquel, & Jouini, 2016).

Number of call arrivals. Time variations for call arrivals impact abandonment rates because direct observation of all interarrival times and service times is not always possible. Goeva, Lam, and Zhang (2014) found that in call centers and clinics, data were available only for system outputs, where sometimes only the waiting time or the queue length data were collected for economic or operational reasons. The data on the input distribution, such as interarrival and service times were limited or unavailable. Goeva et al. (2014) studied the problem of estimating interarrival times and service when only output data was available. Goeva et al. were interested in stochastic simulation to generate the outputs. They proposed an iterative scheme via simulation to estimate interarrival times and service times and found only minor discrepancies between distributions and estimations when they ran over 1,000 iterations. Yet, previous research by Kim and Whitt (2014) provided evidence that even 1000 iterations were not sufficient for call centers and hospitals.

Service systems such as call centers and hospital ERs typically have strongly time-varying arrival rates. Thus, Kim and Whitt (2014) tested the nonhomogenous

Poisson process (NHPP) using a Kolmogorov-Smirnov (KS) test of a Poisson process. The NHPP is a natural model for the arrival process in a queueing model for performance analysis. The KS statistic helps to transform the NHPP into a sequence of random variables that are uniformly distributed and then performing a logarithmic transformation of the data. Kim and Whitt (2014) conducted the final data transformation and considered what form it should take. They conducted extensive simulation experiments to study the power of alternative statistical tests. They concluded that the KS test, without any additional data transformation, was the best test against alternative hypotheses.

Chu, Chen, and Yu (2016) also simulated a stochastic or random process by estimating arrival distributions to find average wait times, queue lengths, and to improve service performance. Chu et al. (2016) proposed a new resource provision approach using service simulation and arrival rate estimation. They clustered days that have similar arrival patterns together. From each cluster, they were able to reveal and separate days having different reasons for time-varying demands of the service. They adopted a business factor model to estimate multi-interval Poisson arrival distributions on daily bases for simulating stochastic processes. By applying simulation on queueing models with multi-interval Poisson arrival processes, they observed stochastic changes of customer waiting time, queueing lengths and number of workers under different service strategies. Chu et al. (2014) then conducted a case study in an electricity service call center to demonstrate adequate resource provision and estimation using historical data to improve real-life operations.

Service rates. In some service operations settings, such as call centers and health clinics, financial or operational managers may collect data regarding only waiting times and queue lengths because data for interarrival and service times are not available (Goeva et al., 2014). Ibrahim, L'Ecuyer, Shen, and Thiongane (2016) stated that traditionally, both researchers and practitioners relied on standard Erlang queueing models to analyze call center operations. But there is an extension of simple models as evidenced by theoretical advances in the recent literature. Ibrahim et al. carried out a large-scale data-based investigation of service times in a call center with many heterogeneous agents and multiple call types. They observed that the service-time distribution depended strongly on the individual agent and they developed stochastic models that accounted for changes over time and correlations across successive days or weeks. When comparing their models to simpler ones, commonly used in practice, they found that their proposed models had a better goodness-of-fit, both in-sample and out-of-sample. They also performed simulation experiments to demonstrate that the choice of model can have a significant impact on the estimates of standard measures for service quality in the call center. Ibrahim et al. recommended further research experimenting with nonparametric functions for trends to evaluate similar alternative models with daily or intra-daily random effects when modeling individual service times. Their more detailed call-by-call dataset better tested how models exemplified entire distributions of the individual service times in the system. The new and realistic service time models can help managers evaluate performance measures such as service levels and average waiting times, for constructing optimal work schedules for agents, and routing calls according to the stochastic algorithms (Ibrahim et al., 2016).

Gong and Li (2014) found that when customers heard the service time information immediately upon arrival to the queue; they waited longer with knowledge of their estimated wait time with periodic updates. The abandonment rates decreased when the prompts notified them of shorter waiting times, and when patients observed an increased service rate. Batt and Terwiesch (2015) detailed how pricing and queueing delays had an impact on the customer's behavior and the rate of arrival. They showed how the flow of patients in and out of the waiting room influenced abandonment where arrivals increased LWT and departures decreased LWT. Batt and Terwiesch found that when new patients arrived in the ER waiting room, the patients in the waiting room were more likely to LWT when new patients arrived after them. Patients responded differently with first-come-first-serve (FCFS) priority. For example, observing an additional waiting room departure that maintained the FCFS order reduced the probability of abandonment by 0.6 percentage points, equivalent to a 19-minute reduction in wait time.

Baumann and Sandmann (2017) considered multi-server tandem queues where both stations had a finite buffer and all service times were phase-type in distribution. Arriving customers entered the first queueing station if buffer space was available and continued through each phase of service if space was available. Baumann and Sandmann provided an exact computational analysis of various steady-state performance measures such as loss and blocking probabilities. They provided numerical results for their representative examples. Van Houdt (2012) also studied Markovian multi-type queues with customer impatience. He introduced an adaptive arrival process and analyzed the adaptive queue. Van Houdt explored an adaptive queueing system where different types of customers with different arrival types (e.g., Markovian inter-arrival times) and the same customer types were fed to a single server queue using thresholds. Service times were phase-type and depended on the type of customer in service. The way the arrival process changed its state after generating a specific customer was dependent on whether the customer was accepted or rejected. Van Houdt (2012) considered Markovian multi-type queues with customer impatience a subclass of the queues and developed a numerical method to determine the probability of abandonment and the waiting time distribution. For general customer impatience, numerical examples showed accurate approximate results. He included numerical examples with adaptive sources that modeled certain types of admission. Also, he found that congestion control determined upper and lower bounds of continuous waiting time distribution to the relative probability of abandonment.

Priority of service. It is imperative to prioritize service to meet the needs of all types of customers to maintain a competitive advantage in business and avoid business loss. Legros et al. (2016) observed the value of offering a callback option to minimize costs related to caller abandonment in congested situations and large call centers. Yu, Benjaafar, and Gerchak (2015) examined a preemptive priority policy in queueing systems with finite service rates. According to Bhat (2015), the priority assigned to a class of customers is either preemptive or not preemptive. If a customer preempts another customer, the lower priority customer's service is interrupted to serve the higher priority customer. When preemption of service is permitted, the service to the preempted customer will resume after the priority customers are served. Yu et al. (2015) stated that organizations decide on the service rate capacity to minimize service-level delays. Organizations can decide to operate shared facilities, but must also decide on a scheme for sharing the capacity cost. Yu et al. formulated their research problem as a cooperative game and identified settings under which capacity sharing is beneficial. They determined a cost allocation that is the core of the FCFS policy or optimal priority policy. Yu et al. determined that capacity sharing may not be beneficial in settings where organizations have service variabilities. They filled a gap in the literature regarding the nature of the optimal priority policy in the presence of both delay costs and service level requirements. When certain types of customers preempted others, causing interruptions in their service, there was a challenge in terms of routing the callers that did not have equal service requirements.

Jouini, Akşin, Karaesmen, Aguir, and Dallery (2015) examined the problem of calculating customer delays for customers with different service level requirements (classes). Jouini et al. (2015) studied delays experienced by customers with different priorities. They modeled the queueing system in Kendall's notation as an $M(t)/M/s(t)$ queue with priorities, thus ignoring some of the real features like abandonments and retrials. They proposed two delay estimators and tested the estimators in a series of simulation experiments. Jouini et al. made use of the actual state-dependent waiting time data from their call center. They estimated the delay announcements to minimize a newsvendor-like cost function. The newsvendor model is used in operations management and applied economics to determine optimal inventory levels. A newsvendor model is characterized by fixed prices and uncertain demand for a perishable product where each unit ordered above demand is lost in potential sales. Jouini et al. found that an Erlang distribution-based estimator performed well for a range of different under-announcement penalty to over-announcement penalty ratios.

Due to the complexity of operations in the ER, it is helpful to look at how scholars and practitioners apply QT to other complex industries such as telecommunications and translate the queueing principles from the call center industry to the healthcare industry. According to Carmen and van Nieuwenhuyse (2014), call center and ER settings are similar because they both have time-varying arrivals and it is difficult for customers to estimate their expected delays in both environments. Therefore, researchers may use studies on call centers to address the lack of analytical models that are available for the LWT problem in the ER. Due to the limited availability of QT applications in ER literature, it was necessary to include the use of QT in call centers as part of this research effort.

LWT

Patients LWT for many reasons. The most common reasons patients LWT are long waiting times (see Abo-Hamad & Arisha, 2013; Bellow & Gillespie, 2014; Liu et al., 2014; Lucas et al., 2014; Pimental & Barrueto, 2014; Sharieff et al., 2013; Tropea et al., 2012) and overcrowding (see Sharieff et al., 2013; Wiler et al., 2013). ER overcrowding is a worldwide problem that occurs when the demand for ER services exceeds available resources (Higginson, 2012; Khalifa & Zabani, 2016). According to

Fayyaz, Khursheed, Mir, and Mehmood (2013), LWT is the best indicator of ER overcrowding.

Non-queueing predictor variables. The next section includes a discussion of non-queueing predictor variables of LWT found in the literature. I divide the non-queueing variables into patient-specific variables and hospital-related variables. Although the concentration of my research effort is on queueing related variables, it is valuable for hospital leaders to become familiar with both patient-level and organizational-level variables that are relevant to LWT.

Patient-level variables. There are patient characteristics that are predictive of the LWT dependent variable. Carron et al. (2014), Crilly et al. (2013), and Tropea et al. (2012) found a correlation between younger age and LWT. Crilly et al. indicated the median age of LWT patients was 25 years old, (*IQR* 18-38), while the median for the group that waited for treatment was 32 (*IQR* 19-54, $p < 0.001$). Tropea et al. compared patient-level characteristics of those whom LWT and those who completed treatment and found that patients 15-24 years of age had the highest LWT (20.1%, $p < 0.0001$) followed by patients 25-34 years of age (18.7%, $p < 0.0001$). The patient's gender was also a subject of discussion in the LWT literature. For example, Crilly did not find significance in gender ($p = 0.48$), but Clarey and Cooke (2012) indicated that 62% of LWT patients were males. Carron et al. (2014) reported only a slight predominance of male patients LWT, while Tropea et al. pointed out that 52.6% of LWT patients were males. Although the researchers have made associations between younger patients, and possibly that male patients more frequently LWT, they did not make any attempt to explain why the demographic factors were significant.

Organizational-level variables. Anderson et al. (2016) hypothesized that larger volume, urban, non-profit hospitals would have worse LWT and longer ER length of stays. Handel et al. (2014) conducted multiple regression (MLR) analysis with a sample of 445 hospitals taken from the Emergency Department Benchmarking Alliance database and found not-for-profit hospitals had a higher association with patients LWT. For-profit status was associated with a statistically significant decrease in LWT (Anderson et al., 2016). Pines, Decker, and Hu (2012) found higher LWT in academic medical centers located in Metropolitan Statistical Areas. There are obvious difficulties in accepting the reliability of data from secondary sources. For example, there is no way to ensure the accuracy of information in more massive databases. Nevertheless, these studies provide enough insight to indicate that policymakers should consider hospital-level determinants of LWT before inflicting payment penalties on hospitals that serve vulnerable populations.

Queueing predictors of LWT. The next section includes a review of the variables related to QT. The queueing variables include the daily arrivals, staffing, triage time, ESI, rooming time, and DTPT. The order of the variable presentation is similar to the way patients progress through the average ER. They arrive at the ER, the number of servers (NOS) may determine the amount of time that elapses before they receive a triage evaluation. Then, they are assigned an ESI level by the triage nurse. Next the staff escorts them to a treatment area, and finally, they await medical screening by a provider.

Daily patient arrivals. There is an association between increased numbers of patients who LWT and high ER census and overcrowding. Bergs et al. (2016) posited that a common misconception is that the overcrowding problem is related to patients making unnecessary or inappropriate ER visits. Nagree, Gosbell, McCarthy, Moore, and Mountain (2013) found that it was not the number of low acuity patients that led to overcrowding, but other factors such as lack of inpatient beds, an increase in elderly patients, complex patients from residential facilities, and more mental health crisis patients. Casalino et al. found a significant linear correlation between the number of daily arrivals and ER length of stay (p = 0.0002, r = 0.268). However, Anderson et al. (2016) found no significant relationship between annual patient volumes and LWT (p = .16). Other researchers have found evidence suggesting that higher volume ERs have a pattern of higher LWT rates (Handel et al., 2014; Pines, Decker & Hu, 2012; Tropea et al., 2012). There were higher rates of LWT in higher volume ERs (OR = 2.20, 99% CI = 2.15 to 2.26) especially in hospitals with more than 200,000 yearly ER presentations (Tropea et al., 2012). Another queueing factor that may influence LWT is the direct care staff available to care for patients.

Staffing. There is a significant amount of existing literature regarding the impact of staffing levels on LWT rates. Brown et al. (2012) found on days where the RN schedule was less than 90% full due to call-outs or poor scheduling, LWT rates were 2.4 times more likely to be high. Anderson et al. (2016) used regression modeling and found no significant association between RN staffing and LWT (p = .06), although there was a significant association between physician staffing and LWT (p = .05). These results provide valuable insights that, rather than increasing staffing numbers, it may be more efficient to make changes in the ER process to improve LWT rates.

Hospital leaders can implement operational changes to successfully decrease LWT without increasing any working staff or working hours. Khalifa and Zabani (2016) found the addition of a fast track and internal waiting area reduced the LWT rate from 17% in 2014 to 9% in 2016. Huang et al. (2013), after adding a clinical assistant, LWT went from 329 in the control period to 242 patients during the case period (p = 0.004). Niyirora and Zhuang (2017) introduced a variation of the square root staffing rule and used Pontryagin's maximum principle to calculate the optimal number of providers to lower waiting times and staffing costs. In conclusion, hospital leaders may be able to increase efficiency and throughput by reorganizing or redistributing staff, not necessarily by adding more staff.

Triage time. Patients leave the ER before triage for a variety of reasons. Many patients leave because the triage nurse is taking too long to triage other patients. Lengthy triage occurs because triage is no longer an area where patients are quickly sorted to evaluate the urgency of care (Scrofine & Fitzsimons, 2014). According to Christensen et al. (2016), triage has evolved into a place for gathering mandatory screenings, medication lists, full vital signs, and initiating protocols and treatments. Therefore, patients' expectations of a timely greeting and a quick assessment of their complaint or injury cannot occur because one triage nurse may have responsibility for 30 to 40 waiting patients (Venella, Papa, & Baren, 2012). A nurse that is skilled and trained for triage can judge immediately on a patient's appearance if the patient is low, medium, or high acuity and route them to the appropriate care area within a few minutes. However, quick triage is not a policy or procedure that ERs commonly exercise.

Another common reason patients leave the ER before triage is that they see how crowded the waiting room is and they decide to go. One easy method of telling if a patient LWT before or after triage is to identify whether or not the nurse has documented an ESI level on the medical record. For example, if an ESI score is missing from the chart, this is a clear indication that the patient did not receive a triage evaluation before leaving the ER. Van der Linden, Meester, & van der Linden (2016) found patients were twice as likely to leave the ER during periods of crowding and when they had to wait more than 10 minutes to see the triage nurse. Van der Linden et al. used an occupancy ratio (total number of ER patients/number of ER beds, occupancy ratio >1 was an indication of crowding) for a sample of (n = 49,539). To illustrate, in a case of an ER with 20 beds or treatment areas, with a total of 50 patients in the ER and waiting room combined, the ratio of 2.5 would indicate a period of crowding. During periods of overcrowding, van der Linden et al. found ESI acuity levels missing from 2.2% of records and missing from only 1.6% of records when the occupancy ratio was < 1 (p < .001). Patients who arrived during crowding did not meet the triage target of 10 minutes when compared to patients who came during non-crowding (49.7% vs. 24.9%, p < 0.001).

ESI. Acuity level was found to be a strong predictor of LWT in many studies. Crilly et al. found lower acuity patients had higher odds of LWT; ESI4 (*OR* 2.76, 95% *CI* 2.60-2.93) and ESI5 (*OR* 3.93, 95% *CI* 3.51-4.37). Likewise, in another study, 63.4% (n

= 130,202) of LWT patients were ESI4 in comparison to 54.7% of patients who completed their visits. Whereas, for ESI5 patients, 30.3% LWT in contrast to 18.8% of ESI5 patients that completed their ER visits (Tropea et al., 2012). Clarey and Cooke (2012) found that lower acuity patients had a greater tendency to LWT. Similarly, Tropea et al. (2012) using logistic regression, found nonurgent patients had the highest LWT rates (*OR* = 8.21, 99% *CI* = 8.00 to 8.43).

Ashour and Kremer (2013) developed a triage algorithm using fuzzy analytic hierarchy process (FAHP) and multi-attribute utility theory (MAUT) to rank patients according to chief complaint, age, gender, pain level, and vital signs. Using discrete event simulation (DES), Ashour and Kremer compared the traditional ESI system with the FAHP-MAUT algorithm. Ashour and Kremer recommended the use of a FAHP-MAUT algorithm which used quantitative measures to assign a priority for each patient, rather than the ESI algorithm which relied on nursing judgments. The ESI is a nominal level of measuring patient acuity, and the nurse must place each patient into one category. There is no way to categorize the priority of patients within each category. For example, ESI3 patients are often the highest LWT category, with the longest waits because many ER policies do not allow ESI4 and ESI5 to have providers see them in fast track (Soremekun et al., 2014). It is difficult to tell from the extant literature, but the ERs with fast tracks may have longer waits for ESI3 patients and those without may have longer waits for ESI4 and ESI5. The researchers did not always differentiate whether the study ER had a fast track, so researchers might consider fast track as a confounding variable.

Zhao (2017) studied advanced nursing protocols to reduce LWT rates and did not find a statistical significance in LWT rates before and after the implementation, days with protocols (41/575, 7.13%) compared with days without protocols (46/611, 7.52%, p=0.07). However, Zhao did note that the use of advanced protocols had an impact on the LWT rates among specific ESI levels. On days where nurses used the advanced triage protocols, there were higher LWT among the lower triage acuity levels (M = 3.7, SD = 0.7) versus days before the nurses were using the advanced protocols (M = 3.6, SD = 0.7, t = -6.3, p < .001). Before the implementation of protocols, approximately one third (n =15) of LWT patients were ESI3, and post-implementation the rate of LWT for ESI3 patients was 24.4% (n =10; $\chi 2$ =10.1, p = .001). ESI4 patients comprised 65.2% (n = 30) pre-implementation and 61.3% post-implementation (n = 25; $\chi 2$ = 6.7, p = .009). The ESI5 patients experienced the most significant negative impact between pre-implementation and post-implementation of the protocols (2% vs.10.2% respectively, $\chi 2$ = 71.5, p < .001). Given these results, Zhao suggested having a provider in triage to quickly move the lower acuity patients in and out of the ER which may eliminate the high proportion of LWT rates for lower acuity levels.

Rooming time. Pielsticker et al. (2015) analyzed the relationship between door-to-room-time (DTRT) and LWT at a 700-bed hospital. Pielsticker et al. considered LWT goal met if the daily LWT was under 1% and the authors divided the mean into a dozen ordinal time slots. There was a significant association between DTRT slots and the chances of meeting the LWT goal (p < 0.001). Pielsticker et al. determined that on study days when mean DTRT was within 20 minutes, they met the LWT goal (87.5% of study days). When the DTRT was $\leq$35 minutes, they met the LWT goal less often (77% of study days). Furthermore, prolonging rooming times to longer than 35 minutes was associated with a significant drop in meeting the LWT goal in a multivariate logistic regression model with 95% confidence intervals. The evidence is suggestive that for each incremental increase in rooming times, the LWT risk also increases. Rogg, White, Biddinger, Chang, and Brown (2013) implemented a physician triage screening program called Supplemented Triage and Rapid Treatment (START) and included the outcome measures, ER length of stay, LWT, DTRT, and number of patients discharged directly from START. Despite a 12% increase in ER volume over the 4-year study period (researchers examined data for one year before implementation of START and three years after implementation), there were significant improvements in all of the outcome measures. The median length of stay decreased by 56 minutes/patient ($p < 0.0001$). The LWT rate dropped significantly (4.8% to 2.9%, $p < 0.0001$). The number of patients discharged without needing a bed increased from 18% to 29% and the median DTRT decreased from 18.4 minutes to 9.9 minutes ($p < 0.0001$). Hospital leaders may decrease LWT by determining cutoff points for patients' willingness to wait for a room or by implementing a START program.

DTPT. The implementation of a split flow model, a medical provider in triage, and simple changes in ER design and process are methods to reduce DTPT and subsequently LWT rates. Abdulwahid, Booth, Kuczawski, and Mason (2016), in a meta-analysis of comparative studies, found a significant reduction in DTPT when a senior doctor was in triage to identify emergencies and initiate diagnostic testing and treatment (median reduction –15 minutes; *IQR* –7.5 to –18). Similarly, Love, Murphy, Lietz, and Jordon (2012) found that placing a provider in triage reduced DTPT from 75 minutes down to 25 minutes and decreased LWT from 3.6% to 0.9%. Melton, Blind, Hall, Leckie, and Novotny (2016) implemented a physician in triage and immediate bedding. Melton et al. reported LWT was 0.49% after implementation versus 4% before implementing the interventions (difference 3.51 percentage points; 95% $CI = 3.43–3.58$; $p < 0.0001$). Bonalumi et al. (2017) implemented a Super Track to treat low acuity patients and found statistically significant differences in pre-intervention and post-intervention DTPT intervals (Mann–Whitney U=2686474, $p < .001$). Also, the LWT decreased by 40% after implementation of the Super Track. Sharieff et al. (2013) proposed a parallel model of care where physicians and nurses assessed the patient together to avoid the repetition of information. Sharieff et al. only used monitored beds for acute patients and other patients received care in recliners or waited for an available space in the staging area. Sharieff et al. found the DTPT pre-implementation and post-implementation were a mean of 126.7 minutes in 2009 (*SD* 37.03) vs. a mean of 26.3 minutes in 2010 (*SD* 1.17, $p < 0.001$). Simple changes in ER design and process changes can have a significant impact on DTPT.

Transition

The problem of patients LWT is a concern for hospital leaders due to lost revenue and lower patient satisfaction scores. Grounded in QT, the purpose of this quantitative correlation study was to examine the relationship between daily patient arrivals, staffing, triage time, ESI, rooming time, DTPT and LWT rates in the ER. This study consisted of archived data records from a community hospital, located in Connecticut and covered visits between October 1, 2017, and May 31, 2018. I assumed that hospital staff accurately recorded archived data that I used for the study, allowing for reliable results. I believe the sample I chose for my research represents the ER population, and therefore conclusions from my study should apply to other ERs with similar characteristics. As a correlational researcher, I can only demonstrate the ability to predict a relationship between variables. Correlational research is limited in that it does not determine a causal relationship between variables (Simon & Goes, 2013). The scope of this study covered variables relating to queueing theory, and I narrowed the focus to only input factors that impact LWT. I did not include ESI1 patients because the severity of their medical condition limits their ability to LWT. The significance of filling a research gap in QT and LWT is the knowledge that hospital leaders will gain, so every patient can equally experience access to care and emergency resources. Also, hospital leaders will satisfy a significant quality indicator if they learn to reduce LWT percentages. Ideally, no patient would ever LWT, the hospital would receive full payment for all of its resources, and every patient would depart with the highest level of satisfaction. The next section of this study, Section 2, will include the method and design for this study, and then Section 3 will consist of the study results, applications for professional practice and implications for social change.

Section 2: The Project

Section 2 includes information regarding the method and design for the present study. First, I will restate the purpose of the study. Second, I will present my role in the study design, including limitations and how I mitigated these challenges to ensure reliability and validity. Third, I will discuss strategies for gaining access to the participants for the present study, including ethical and legal considerations. Finally, I will expand on the research method as an extension of the Nature of the Study discussion from Section 1, as well as discuss the data analysis plan.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between the predictor variables of daily arrivals, daily staffing, triage time, ESI, rooming time, DTPT, and the dependent variable LWT. The targeted population comprised patients of all ages who visited the participating ER between October 1, 2017, and May 31, 2018. The implications for positive social change as a result of this study, include the potential for ER patients to experience increased satisfaction from the high quality of care and overall better public health outcomes. Hospital leaders may use the information from this study to project the potential for LWT and modify or manage the staffing levels, and times patients must wait for triage, room placement, and DTPT to decrease the rate of LWT in the ER.

Role of the Researcher

According to Simon and Goes (2013), in theory, the researcher does not have a role in quantitative research. In other words, the participants are independent of the researcher. Quantitative analysis contrasts with qualitative research, where the researcher plays an active participatory role in collecting data. In this quantitative correlational study, my position as the researcher was to reduce bias and subjectivity throughout the study process. As a researcher, I did not have any direct interaction with participants as I only collected archival data, analyzed the results, and synthesized the findings with the literature. Because I employed a non-experimental, correlational design, it was vital that I did not draw causal inferences from my study results. Bleske-Rechek, Morrison, and Heidtke (2015) suggested avoiding terms such as consequences, effects, or negative impact in reporting results for non-experimental studies.

I applied some basic principles from The Belmont Report (1979) that a researcher must follow when conducting biomedical and behavioral research with human subjects. Researchers should always have informed consent of participants and maintain the privacy of the research site (Ignacio & Taylor, 2013). There was no informed consent because individuals did not participate in this study. Respect, privacy, and anonymity were necessary to ensure all patient information was kept confidential (Ignatio & Taylor, 2013). My role as a researcher was to have a reliable process where there was no bias in the instrument or assessment tool. Thus, I made my study method standard enough so that other researchers could repeat the process and draw similar conclusions.

Participants

I used archival data to conduct my study, so I did not interact with individual participants. The archival data consisted of a community hospital's ER records for all visits occurring between October 1, 2017, and May 31, 2018. I gained access to the archival data through the hospital administrators after obtaining written permission from the hospital's IRB and hospital administration (see Appendices B and C). The data came from a for-profit, 156-bed acute care hospital, which serves both adult and pediatric populations in the ER. According to online data from 2016, the hospital had operating revenue of $226.8 million (FY 15) and 1008 employees, of which 396 were physicians. The hospital provided a broad spectrum of services to meet the needs of the community and had 51,903 ER visits last year.

Research Method and Design

Research Method

I employed a quantitative methodology while conducting this study. Park and Park (2016) advised that the objectives of the quantitative method are to predict and control social phenomena. Additional goals are measuring, evaluating, and generalizing findings to a population, allowing other researchers to replicate the results quickly. In quantitative studies, researchers use numerical data to assess the presence of statistically significant relationships or differences (Howell, 2013; Tabachnick & Fidell, 2013). A quantitative method should align with the research question, procedures, and the intended statistical analysis (Field, 2013).

Other optional methods to conduct a study include qualitative and mixed methodology. Qualitative researchers seek to answer questions by collecting individual or group data about the lived experiences of people and formulating conclusions inductively (Moon et al., 2013). Qualitative research involves hermeneutic understanding and researcher-driven thematic analysis of patterns that emerge from the interview process (Gergen, Josselson, & Freeman, 2015). Conversely, quantitative researchers use a deductive approach, starting with specific hypotheses and then using numerical data to support the assumptions (Moon et al., 2013). I collected statistical data to answer the research question for this study. Quantitative methodology was the most appropriate method to establish statistically significant relationships or determine correlations among variables. Researchers use mixed methods to integrate qualitative and quantitative approaches for data collection, analysis, and interpretation (Powell, Mihalas, Onwuegbuzie, Suldo, & Daley, 2008). My study does not have any qualitative elements, so a mixed methods approach was not appropriate for my study. According to Field (2013), in mixed methods research, there is a focus on quantified data to inform findings related to testable hypotheses.

Research Design

Quantitative research designs include, but are not limited to, correlation designs, experimental designs, descriptive and quasi-experimental designs (Bleske-Rechek et al., 2015; Hudson & Llosa, 2015). According to Hudson and Llosa (2015), researchers choose correlation designs to determine relationships between variables, whereas the desired outcome of experimental design is to explain causality between variables. Correlational analyses are appropriate when the researcher intends to assess associations between variables without manipulating the variables of interest (Field, 2013; Tabachnick & Fidell, 2013). Accordingly, I employed a correlation design. Correlation design was appropriate for this study because it was not possible to randomly assign participants to groups or to manipulate the study variables.

A critical aspect of experimental research is that researchers can manipulate the levels of the independent variables (Tabachnick & Fidell, 2013). Within experimental studies, researchers may control the conditions of the study and randomly assign participants to groups for comparison (Field, 2013). Experimental studies typically involve intervention or treatment where the researcher intends to assess the influence of such treatment (Cohen, Manion, & Morrison, 2013). These aspects of experimental research did not align with my study, so I did not use an experimental approach.

Descriptive designs facilitate an exploratory investigation to describe the variables or constructs of interest (Bleske-Rechek et al., 2015). Within quantitative descriptive studies, researchers typically report descriptive statistics to define the selected variables within the sample (Howell, 2013). Frequencies and percentages are the appropriate descriptive statistics for categorical variables, while means and standard deviations are suitable for continuous variables (Field, 2013). A descriptive approach was not necessary because I did not intend to describe the variables associated with LWT. However, I did include the mean and standard deviation for each variable in the results section to provide additional information to the reader (see Table 3).

Finally, quasi-experimental studies involve the grouping of participants (Campbell & Stanley, 2015). A critical difference between experimental and quasi-experimental studies is a lack of random assignment to groups (Campbell & Stanley; Cook, 2015; Valenzuela, Arriagada, & Scherman, 2014). A quasi-experimental design was not suitable because I was not grouping or categorizing individuals within this study.

Population and Sampling

The target population consisted of all archival data records of individuals who visited a community ER in CT between October 1, 2017, and May 31, 2018. I conducted a census, gathering all available archival data for the variables of interest during the selected time frame. Using the data for approximately 160 days, I assessed the relationship between the predictor variables of daily arrivals, daily staffing, triage time, ESI, rooming time, DTPT, and the dependent variable LWT.

A census approach incorporates every available observation within the target population (Singh & Masuku, 2014). Census approaches minimize issues related to sampling error because they comprise all the available observations in the dataset (Singh & Makusu). Additionally, census approaches allow researchers to avoid problems related to the representativeness of a sample because the study does not rely on a subsection of the population to draw inferences (Moser & Kalton, 2016). Census approaches are weaker because of the potential for undercounting of specific sections of the population (Singh & Makusu). A census approach was feasible for this study because the target population was small, and I collected all available data points for visits between October 1, 2017, and May 31, 2018.

Sample size calculation is critical in quantitative analysis. Quantitative studies typically require larger sample sizes to achieve statistical validity (Field, 2013). Additionally, larger sample sizes that are representative of the target population enhance the generalizability of the inferential statistics (Mullinix, Leeper, Druckman, & Freese, 2015). I conducted a power analysis using G*Power to determine the sample size necessary to achieve statistical validity within this study. G*Power is a statistical software package used to calculate sample size and conduct a power analysis (Faul, Erdfelder, Buchner, & Lang, 2009). Using G*Power version 3.1.9 software, I conducted an a priori power analysis to determine the minimum sample size required for the study. For the G*Power analysis a medium effect size (f^2= .15), alpha = .05, and power of .80 were the input parameters. I used the established parameters for MLR with six predictors and determined that the minimum sample size required was 146 participants, or units of (see Figure 1). I collected data for 244 days to make sure I would have a complete sample. After eliminating 85 days with data missing for one or more variables, I was able to exceed the necessary units of analysis, a total of 159 days. After removing the outliers, the final sample was *N* = 154.

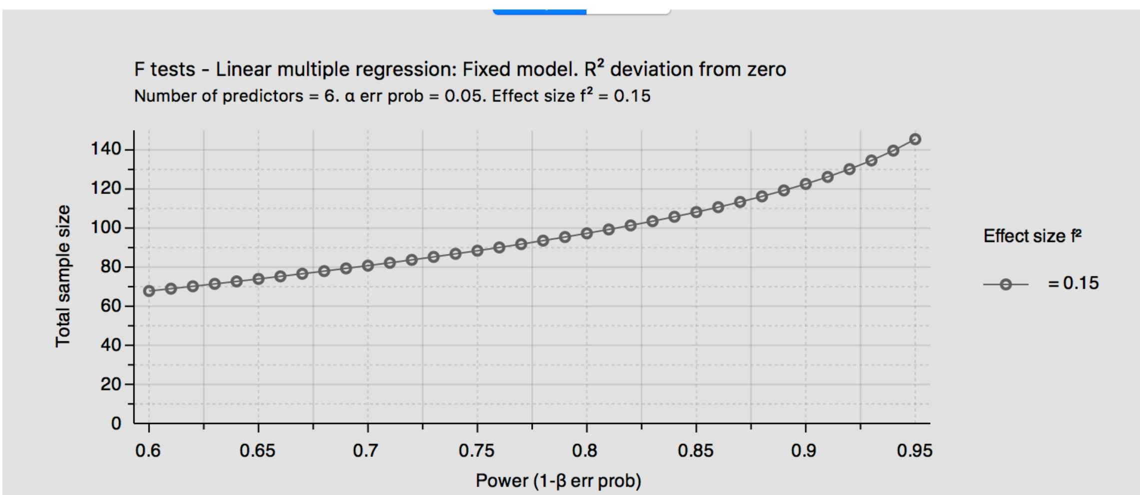

Figure 1. Graphical depiction of power analysis. A statistical power analysis using G*Power 3.1. Adapted from Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009).

Ethical Research

According to Ignacio and Taylor (2013), the most common ethical problems in research consisted of three main branches: Privacy/confidentiality, informed consent, and researcher-participant relations. HIPAA is an essential consideration in healthcare research (LoBiondo-Wood & Haber, 2014). I needed a password to collect the data for my study, and all information was kept strictly confidential. Also, I removed all hospital identifiers from printouts that I took home from hospital grounds (e.g., staffing sheets). I plan to keep all paper records secured for at least 5 years in a locked filing cabinet because the staffing sheets have employee information on them. After the 5-year storage minimum is met, I will shred all paperwork related to my study.

I collected archival data, so there were no procedures for participant withdrawal, participant informed consent, or incentives. I received only de-identified numerical data, so there were no concerns over protecting patient identifiers such as names or contact information. However, I have safeguarded employee information such as names that were on the staffing sheets (there are no other personal identifiers on staffing sheets besides the employee's names). I withheld details and descriptions in the doctoral study that would permit a reader to identify the hospital. I signed confidentiality and data use agreements, so hospital leaders had informed consent regarding my study.

The IRB approval number for this study is 06-21-18-0460492. I followed the IRB requirements and articulated the data collection steps during the proposal phase. Appendices B and C contain the confidentiality agreement and data use agreement (originals prior to obtaining signatures to protect hospital identity). There were no names or contact info recorded in the research records. The research procedure included all possible measures to avoid direct or indirect disclosure of the study hospital. There were no psychological or physical risks to address before or during the study. I was an employee of the hospital and acknowledge this as a relationship or professional risk. The hospital did not suffer from loss of privacy, economic decline, or damage to professional reputation as a result of my research there. I proactively managed the potential conflict of interest and maintained a professional relationship with administrators. I did not conduct any data collection or work related to my research on hospital time to cause a financial conflict of interest. All data collection took place in my time. There was no risk to objectivity because everything was numerical data, but I avoided bias in the interpretation of the results. There was no pressure to get a specific result from this study to benefit the organization or for my professional gains. I did not overlook essential data or alter my perception of critical observations as I collected, analyzed, or interpreted the data. The research design had a minimal burden on the institution; minimal time and effort were required from the business administrator and medical director to obtain the information I needed for this study and for review of my results for validity.

Most of my variables were standard metrics that were collected daily and stored in a database. These variables only required that the hospital administration gave me electronic access to triage times, DTPT, daily patient arrivals, and LWT numbers according to ESI level. The medical director provided me with the staffing of physicians and physician assistants (mid-level practitioners), while the clinical staffing coordinator provided printouts of all nursing and patient care technician staffing. The administrators for the study hospital provided the signed Data Use Agreement granting permission for all appropriate data access, facility use, and staff time for research purposes. I received approval from the hospital IRB and the Walden University IRB to conduct my research prior to data collection.

Data Collection – Instruments

I did not collect any primary data for my study. I gained access to information that clerical staff gathered at the study ER and analyzed the pre-existing data for my research. The electronic health record (EHR) contained all data for the predictor variables and the dependent variable. According to Ward et al. (2014), the federal government offered $17 billion as an incentive for hospitals and providers to adopt and use EHRs, and organizations with noncompliance by 2015 would receive financial penalties. Therefore, accuracy and reliability of the records were necessary for the hospital. Quality metrics are reportable to regulatory agencies, such as The Joint Commission and Center for Medicare and Medicaid, which perform random audits of the information (Agency for Healthcare Research Quality [AHRQ], 2014). Many of the variables in this study were hospital metrics required by regulatory agencies to prove the adequacy of performance measures. I will describe each variable and identify their scales of measurement below. I will also discuss the derivation and meaning of each variable. Appendix B presents permission to use the data. The Emergency Department Benchmarking Alliance (EDBA) provided standardized definitions for performance measures to allow for a more accurate comparison of ERs in research and practice (Wiler et al., 2015). I used the EDBA definitions of measurement for service time standards and measures of ER utilization.

Daily Patient Arrivals

The daily patient arrivals, a ratio scale of measurement, included the number of patients arriving at the ER per day. According to Wiler et al. (2013), most hospital administrators track arrivals as an annual census. However, for this study, days are the unit of analysis. I collected a daily number of patient arrivals (NOPA) to accommodate the unit of analysis for the data within this study. NOPA was a predictor variable for this study.

Staffing

The number of servers (NOS) was the number of daily ER staff involved in direct patient care. I collected the staffing variable, a ratio measurement, by counting the number of employees engaged in direct patient care in the ER each day. Wiler et al. (2013) advised that administrators divide ER staffing into the following categories: full-time physician equivalents (FTEs), physician assistant FTEs, advanced practice nurse FTEs, nurse FTEs, technician FTEs, pharmacist FTEs, social work FTEs, case manager FTEs, and other administrative FTEs. I only counted direct care staff FTEs including physicians, advanced practice clinicians, patient care technicians, and nurses working in the ER for each day during the study period. NOS was a predictor variable in this study.

Triage Time

I measured the door-to-triage-time (DTTT), a ratio level, as the number of minutes between the patients' arrival to the ER, and the start of triage. The DTTT is the number of minutes that elapse between arrival and triage evaluation by the RN. DTTT was a predictor variable for this study.

ESI

ESI is as an ordinal level of measurement ranging from ESI1 (*most urgent*) to ESI5 (*least urgent*). The nurse determines the ESI level by evaluating the patient's need for immediate intervention if they are high risk, and the number of resources the patient requires for care (Mistry et al., 2017; Gilboy et al., 2012). However, for this study, ESI measurements reflected a ratio level of measurement. I calculated the number of patients that LWT for each ESI level. Although there are 5 ESI levels, I dropped ESI1 patients because there was a 0% rate of ESI1 patients that LWT. Therefore, this study only included ESI2, ESI3, ESI4, and ESI5.

Rooming Time

The next variable I collected for my study was rooming time or door-to-room-time (DTRT), which represented the time it took for the patient to reach a treatment area after check-in. Wiler et al. (2015) defined ER treatment spaces as ER rooms, ER non-room bed-spaces, ER non-room chair spaces, and ER observation unit treatment spaces. For this study, DTRT was a ratio measurement. I assessed DTRT as averages in minutes for each day during the study period. DTRT was a predictor variable describing the time it took for the patient to arrive to any of the above treatment areas.

DTPT

The DTPT is the amount of time it takes for the provider to have initial contact with the patient for diagnostic evaluation (Wiler et al., 2015). For this study, DTPT was a ratio measurement. I measured the DTPT as daily averages in minutes for each day during the study period. DTPT was a predictor variable for this study.

LWT

I measured the number of patients who LWT as the number of patients who left the ER before having an evaluation by a medical provider. For this study, the ratio level measurement was the number of patients who departed either before or after triage but were not seen by a provider. This number does not include elopements or patients that left the ER against medical advice (AMA) or after the provider evaluation. I excluded days, from the original data set that did not have an ESI level assigned for the LWT.

Data Collection Technique

I accessed archived hospital records for ER visits between October 1, 2017, and May 31, 2018. Archival data collection comprises the secondary analysis of existing data (Schulz, Hoffman, & Reiter-Palmon, 2005). According to Schulz et al. (2005), the advantages of archival data collection techniques include savings of resources, ease of data transfer and storage, and the availability of larger samples, longitudinal data, and cross-cultural data.

The advantage of this technique is practicality due to time constraints. The disadvantage is that the data is not random and may not represent the behaviors of the larger population. I received the printouts of daily staffing numbers and transferred the information into an Excel spreadsheet. I accessed all the other variables for my study in the EHR. I collected data manually for 244 days covering all visits between October 31, 2017, and May 31, 2018. The staffing sheets contained only employee names, hours that they worked, and information for sick-calls. I will save the printed information in a locked filing cabinet for no longer than 5 years, and then I will shred paper records (to protect employee privacy). I used statistical analyses to evaluate the level of confidence, risk and levels of precision for my study.

Data Analysis

The research question for this study was: What is the relationship between daily arrivals, daily staffing, triage time, ESI, rooming time, DTPT and LWT rates in the ER?

H_0: There is no relationship between daily arrivals, daily staffing, triage time, ESI, rooming time, DTPT, and LWT rates in the ER.

H_1: There is a relationship between daily arrivals, daily staffing, triage time, ESI, rooming time, DTPT, and LWT rates in the ER.

I used SPSS version 24.0 for Windows to perform MLR analysis. Researchers use MLR to assess the predictive relationship between a combination of independent variables and one predictor variable (Pallant, 2016). According to Salkind (2017), in multiple regressions, the combination of variables should predict Y better than any one of the variables would predict alone. When discussing MLR, authors sometimes refer to the dependent variable as a response variable, criterion variable, or outcome variable (Cohen, Cohen, West, & Aiken, 2013; Pagano, 2013; Pituch & Stevens, 2016; Salkind, 2017; Tabachnick & Fidell, 2013). Whereas, independent variables are also known as predictor variables (Cohen et al.; Pagano; Pituch & Stevens; Salkind; Tabachnick & Fidell). According to Cohen et al., there are three types of regression analyses a researcher may choose to conduct depending on the nature of the study: simultaneous, hierarchical, and stepwise. In simultaneous multiple regression, all the predictor variables carry the same footing, and there is no logical or theoretical basis for considering an independent variable to have priority over another independent variable (Cohen et al., 2013). Simultaneous MLR is appropriate for my study because I am examining how several independent variables contribute to the prediction of the dependent variable in a group and not analyzing the variables in individual blocks. MLR allows the researcher to examine the collective effect of the predictor variables on the criterion variable while reducing the risk of committing a Type I error (Pituch & Stevens, 2016).

I determined that an alternative approach such as a hierarchical MLR was not best for my study. With hierarchical MLR, predictors are cumulative according to an order that the researcher pre-specifies using the purpose and the logic of the research as a guide (Cohen et al. 2013; Tabachnick & Fidell, 2013). Furthermore, a researcher uses hierarchical regression to confirm the combination of predictor variables that support a theory (Ray-Mukherjee, Nimon, Morris, Slotow, & Hamer, 2014). Hierarchical MLR approach was not appropriate for my study because I did not pre-determine an order of inclusion of variables into the regression model supporting a specific theory.

Before conducting the simultaneous MLR analysis, I cleaned the dataset by screening for outliers in the continuous variables within the archival data. Field (2013) recommended calculating z scores to represent the distance of each value of the continuous variables from the mean of the variable. According to Stevens (2009) and Tabachnick and Fidell (2013), z scores with values higher than ± 3.29 are considered outliers, and the researcher should address them appropriately. Therefore, I removed those cases from further analysis. For this study, the only missing information from the original data collection included days where patients left before triage and nursing did not assign an ESI level. The cases without assigned ESI levels were excluded from the dataset because ESI level is a predictor variable for the study.

The researcher must assess the assumptions of MLR analysis including multicollinearity, normality, linearity, and homoscedasticity (Pallant, 2013; Stevens, 2009; Tabachnick & Fidell, 2013). Furthermore, many authors suggest using variance inflation factors (VIF) to ensure the absence of multicollinearity (Field, 2013; Pallant, 2013; Tabachnick & Fidell, 2013). VIFs greater than 10 are evidence of multicollinearity, and a Pearson correlation analysis is useful to determine which variables are highly correlated. Field (2013), Pallant (2013), and Pagano (2013) suggested removing one predictor from the regression model for any pairs of predictors with a correlation coefficient of .9 or above. Pallant advised that multicollinearity and singularity are contributors to a poor regression model and the researcher should address these issues at the start of the study. Following the advice of Pallant, I evaluated the relationship among the chosen predictor variables for this study.

Pallant (2016) recommended the interpretation of residual scatterplots in IBM SPSS to assist the researcher in checking the normal distribution of scores on the dependent variable. Also, Field (2013) suggested that Shapiro-Wilk tests with p values less than .05 are indicative of a violation of the assumption of normality. Stevens (2009) posited that the MLR is robust to violations of normality with a sample size of greater than 50 observations. Because my sample exceeded 50 observations, my report was robust to any violations of normality.

I screened the residual scatterplots for each regression analysis to ensure that I met the assumptions of linearity and homoscedasticity. The residual scatterplot must show a straight line to indicate a relationship between the predictor and criterion variable in order to satisfy the assumption of linearity (Field, 2013; Tabachnick & Fidell, 2013; Pallant, 2016). To meet the assumption of homoscedasticity, the data points must be approximately evenly distributed around ‘0’ and must be roughly rectangular (Pallant, 2016; Tabachnick & Fidell, 2013).

To report the findings of the MLR analysis I interpreted the *p*-value, adjusted R^2, and *B*. The *p*-value indicates the probability that the observed coefficient is possible if the true population value was zero (Field, 2013). The researcher reports the adjusted R^2 to show the amount of variation in the criterion variable that the researcher might attribute to the combination of predictor variables (Pallant, 2016). The overall regression model was statistically significant, so I interpreted the unstandardized beta coefficient, *B*, for each statistically significant predictor. A researcher uses the unstandardized beta coefficient to assess the change in the criterion variable for each unit increase in the statistically significant predictor variable (Pagano, 2013; Tabachnick & Fidell, 2013).

Threats to Statistical Conclusion Validity

Threats to statistical conclusion validity (SCV) are factors that affect the Type I Error and Type II Error (Cronk, 2016). A Type I Error occurs when the researcher incorrectly rejects the null hypothesis even though it is true (Cronk, 2016; Hales, 2016).

A Type II Error occurs when the researcher incorrectly sustains a false null hypothesis (Cronk, 2016; Hales, 2016). According to Garcia-Perez (2012), these error types are fundamental aspects of statistical decision theory in regards to significance testing. Therefore, the researcher has the potential for either one of the errors to occur. Garcia-Perez advised that the researcher can preserve SCV with a proper analysis of data where the results provide a meaningful probability of accurately answering the research question. My primary goal was to generalize my findings to the broader population following a quantitative scientific method. Garcia-Perez discussed some threats to SCV including reliability of the instrument, data assumptions, and sample size. I will address these risks to SCV as they apply to my study.

Instrumentation Reliability

Instrument reliability was not applicable to this study because I did not use a formal instrument for data collection. Suter and Suter (2015) stated that there is a threat to conclusion validity when the researcher's definition of the construct (operationalization) under investigation does not represent the chosen label. In other words, variations in operational definitions amongst studies may lead to different conclusions. I have made every attempt to standardize my variables according to operational definitions in similar studies cited in the literature review.

Data Assumptions

The researcher can take steps to minimize the common threats to SCV by checking assumptions of statistical tests. According to Cerqueti et al. (2017), bootstrapping is an analytical method to adjust for any possible influences of assumption violations. With the violation of assumptions, the researcher must report the 95% bootstrap confidence (Cerqueti et al., 2017). An assumption of bootstrapping is that the original sample is representative of the underlying population (Neiheisel, 2017).

Sample Size

The branch of inferential statistics allows researchers to generalize about populations considering only a sample and to draw conclusions regarding the relationship between the sample and the population (Powner, 2017). A power analysis was conducted to identify the minimum sample size required to achieve the minimum power of .80. Using the power analysis, I determined that a minimum of 146 cases was necessary for the final analysis, but the final dataset went over the minimum requirement ($N = 154$).

Transition and Summary

In Section 2, I described my role as a researcher in the data collection process. Although I did not have any participants because I am using archival data, I did discuss the application of some basic principles from the Belmont Report and procedures for conducting ethical research. I distinguished the research method as a quantitative study and the research design as MLR analysis, which is correlational. I also included a description of the population and justified the sample size via power analysis. Because there is no specific instrument for the study, I reviewed the collection process for secondary data, as well as the advantages and disadvantages of the secondary data analysis. I described and defended in detail the reasons why MLR analysis was an appropriate choice to answer the research question for this study.

In Section 3, I will present the findings of this study, discuss the testing of assumptions, and provide a summary of QT as it relates to the conclusions. I will also detail how hospital leaders can apply the study findings to address the specific business problem. After the analysis and discussion of the study results, I will suggest implications regarding tangible improvements for social change in the ER and how individuals, communities, and society, in general, can benefit from a solution. Finally, I will recommend useful actions for hospital leaders to make changes and also suggest areas for further research.

Section 3: Application to Professional Practice and Implications for Change

Introduction

In this study, I conducted a simple MLR to assess the relationship between NOPA, NOS, DTTT, ESI, DTRT, DTPT, and LWT. The null hypothesis was that there is no relationship between the predictor variables, NOPA, NOS, DTTT, ESI, DTRT, and DTPT, and the dependent variable LWT. The alternative hypothesis was that NOPA, NOS, DTTT, ESI, DTRT, and DTPT would significantly predict LWT rates in the ER.

Presentation of the Findings

The results of the MLR were statistically significant, with F (9,144) = 2902.49, $p < .001$, and $R^2 = .99$, indicating 99% of the variation in LWT was accounted for by the predictor variables. Therefore, the null hypothesis was rejected. The results of the regression analysis are presented in Table 1. In the final model, ESI2 ESI3, ESI4, and ESI5 were statistically significant to the variation in LWT, $p < .001$. The final predictive equation was: Y = -.068 -0.001 (NOPA) + 0.003 (NOS) + 0.004 (DTTT) + 1.016 (ESI2) + 0.999 (ESI3) + 1.015 (ESI4) + 1.021 (ESI5) + 0.002 (DTRT) + 0.001 (DTPT).

I conducted bootstrapping on the data to decrease the potential for violations using 1,000 samples and a 95% confidence interval (see Table 1). Bootstrapping is a resampling technique that helps the researcher address confidence intervals on variables and decreases the probability that the researcher will make unreasonable assumptions (Efron, Rogosa, & Tibshirani, 2015). The overall regression model was statistically significant, so I interpreted the unstandardized beta coefficient, B, for each statistically significant predictor. A researcher uses the unstandardized beta coefficient to assess the change in the criterion variable for each one unit increase in the statistically significant predictor variable (Pagano, 2013; Tabachnick & Fidell, 2013).

Table 1

Regression Analysis Summary for Predictor Variables

Variable	β	*SE*	*B*	*t*	*p*	Bootstrap 95% CI (β)
(Constant)	-.068	0.13		-.525	.600	[-.323, .187]
NOPA	-.001	.001	-.012	-1.625	.106	[-.003, .000]
NOS	.003	.003	.006	.904	.367	[-.004, .009]
DTTT	.004	.004	.007	1.111	.269	[-.003, .012]
ESI2	1.016	.022	.294	46.387	.000	[.972, 1.059]
ESI3	.999	.008	.851	124.454	.000	[.983, 1.015]
ESI4	1.015	.019	.341	53.016	.000	[.978, 1.053]
ESI5	1.021	.069	.094	14.748	.000	[.884, 1.158]
DTRT	.002	.004	.005	.553	.581	[-.006, .010]
DTPT	.001	.001	.008	.844	.400	[-.001, .003]

Note. $N = 154$

I examined the normal P-P plot for the regression standardized residuals and the scatterplot of the standardized residuals to assess the assumptions of the absence of outliers, normality, linearity, homoscedasticity, and independence of residuals. I screened the plots to ensure that the assumptions were not violated, looking for a relatively straight-line distribution of points extending diagonally from the bottom left to the top right of the P-P plot and a random distribution of the data points in the scatterplot. Examination of these plots indicated the presence of mild violations of the assumptions.

Tests of Assumptions

Multicollinearity. I assessed multicollinearity using the VIF values and made sure there were no outliers by examining the standardized values for each data point. VIF values are calculated and screened to ascertain elevated levels of collinearity among predictor variables (Tabachnick & Fidell, 2012). VIFs ensure the absence of multicollinearity where VIFs greater than 10 are evidence of multicollinearity (Field, 2013; Pallant, 2013; Tabachnick & Fidell, 2013). For my study, values for the predictors met the threshold value of 10; therefore, I satisfied the assumption of the absence of multicollinearity. Table 2 presents VIF values for the predictor variables.

Table 2

Multicollinearity of the Predictor Variables

Predictors	VIF
NOPA	1.53
NOS	1.21
DTTT	1.04
ESI2	1.05
ESI3	1.23
ESI4	1.09
ESI5	1.07
DTRT	2.35
DTPT	2.47

Outliers. The presence of outliers was assessed using standardized values, or *z* scores, for each data point. According to Tabachnick and Fidell (2012), *z* scores higher than 3.29 units from the sample mean are evidence of outliers. I screened and removed five outliers from the dataset. I removed two outliers from DTTT, two from DTRT, and one from LWT. The final dataset consisted of 154 cases.

Normality. I assessed the assumption of normality with a Shapiro-Wilk test. NOPA was a non-significant finding (p = .574). According to Field (2013), a non-significant test (p > .05) indicates that the sample distribution is not significantly different from a normal distribution. However, the results of the analysis indicated that I did not meet the assumption for the variables NOS (p = .025), DTTT (p = .034), DTRT (p = .006), DTPT (p = .000), and LWT (p <.001). Field (2013) advised that the distribution is significantly different from normal distribution when p < .05. Field also advised that, although the Shapiro-Wilk test is a simplistic way of determining normal distribution, it is not the best test of normality for large samples. Stevens (2009) also cautioned that with sample sizes larger than 50 cases, MLR analyses are robust to violations of normality. In summary, I ran the normal P-P plot of the regression standardized residuals (see Figure 2) to assess normality and determined that normality was violated.

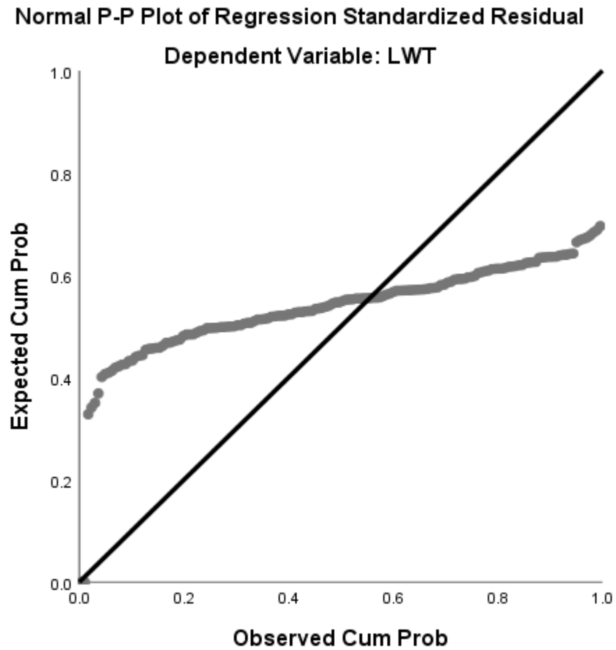

Figure 2. Normal probability plot (P-P) of the regression standardized residuals.

Linearity and Homoscedasticity. I examined the assumptions of linearity and homoscedasticity through screening of the residual scatterplot to assess if the points in the plot were randomly distributed around a mean value of 0 (see Figure 3). The assumption of homoscedasticity was not met because the residual line did not resemble the actual values. I also examined linearity with a screening of the residual scatterplot to assess the presence of any curvature which would indicate a non-linear relationship between the predictor and dependent variables. Examination of the residual scatterplot indicated that the assumption of linearity was met (see Figure 3).

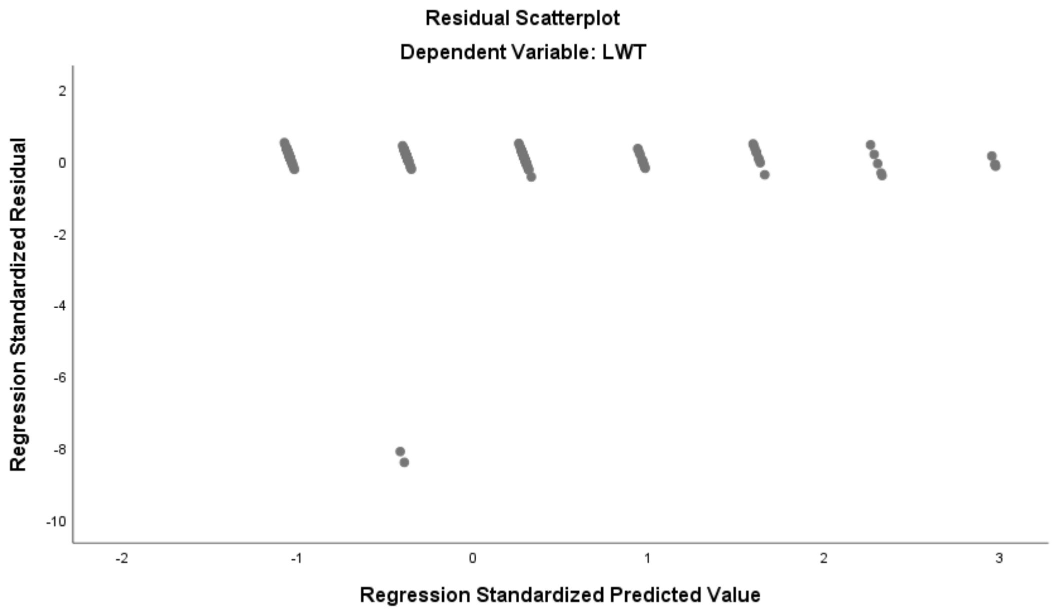

Figure 3. Residual scatterplot for linearity and homoscedasticity.

Descriptive Statistics

I calculated descriptive statistics for the study variables including the mean (*M*) and the standard deviation (*SD*). The *M* is a measure of central tendency computed by dividing the *sum* of all values in the group by the number of values in that group (Salkind, 2017). The *SD* represents the average amount of variability of the data around the mean or the distance from the mean (Salkind, 2017). See Table 3 for the presentation of descriptive statistics.

Table 3

Descriptive Statistics

Variable	*N*	*M*	*SD*
NOPA	154	135.42	16.15
NOS	154	35.43	3.10
DTTT	154	12.11	2.43
DTRT	154	8.90	3.56
DTPT	154	28.48	12.75
LWT	154	1.55	1.50
ESI2	154	0.18	0.44
ESI3	154	1.11	1.28
ESI4	154	0.25	0.51
ESI5	154	0.02	0.14

Theoretical conversation on findings. The findings extend knowledge of QT and relationships among queueing variables. For the ER, LWT in QT resembles impatient customers or abandonment in other industries, such as call centers. One primary objective of this study was to show hospital leaders how QT models might translate to the ER to reduce the phenomena of clients leaving without service. During this research, the one major obstacle I encountered with translating QT from call centers to the ER was the time variation that occurs in the ER, where service times for call centers occur in minutes, compared to hours for the ER. However, there were still many parallels between caller abandonment in call centers and patients who LWT in the ED. Caro et al. (2016) and Hall et al. (2013) have used queueing models, and DES to model abandonment in call centers and these concepts are becoming more prolific for management of patient flow, reducing delays in healthcare delivery, as well as, health technology assessment.

I found in this study that factors such as NOS, NOPA, and DTPT were not significant predictors for LWT. These findings are not consistent with the findings of Ramsey (2018) who found that decreased nursing staffing was a significant predictor of LWT. However, I confirmed the findings of other authors who found acuity level to be the strongest predictor of LWT.

ESI levels were found to be a strong predictor of LWT in this study, where the magnitude of the t value was the greatest for ESI3 ($t = 124.454$), followed by ESI4 ($t = 53.016$), then ESI2 ($t = 46.387$). ESI5 patients had the lowest magnitude ($t = 14.748$). I confirmed the findings of Soremekun (2014) and Deflitch, Geeting, and Paz (2015) who found that ESI3 patients LWT most frequently. This study disconfirmed the findings of Crilly et al. who found lower acuity patients had higher odds of LWT; ESI4 (*OR* 2.76, 95% *CI* 2.60-2.93) and ESI5 (*OR* 3.93, 95% *CI* 3.51-4.37). This study also disconfirmed the findings of Tropea et al. (2012) who determined that 63.4% ($n = 130{,}202$) of LWT patients were low acuity ($OR = 8.21$, 99% $CI = 8.00$ to 8.43). This study confirmed the research of Lucas et al. (2014) who studied LWT rates by triage class and found ESI3 most significant for LWT.

Applications to Professional Practice

Hospital leadership can use this information in professional practice by paying attention to the tendencies of specific ESI levels to LWT. Precisely, the reasons why ESI3 patients are the most likely group of patients to walk out of the ER without service. Hospital leaders may apply the findings of this research by using strategies to decrease LWT among ESI3 patients. This research confirms the magnitude of LWT rates for ESI3 patients that are impacted by long waits. Hospital leaders can help make ESI3 patients a less vulnerable sub-population of patients and affect massive social change (by decreasing harm that could result from not getting medical care).

Implications for Social Change

Patients who LWT are a high-risk group for medical and legal reasons, and operational outcomes, including patient satisfaction (Pielsticker et al., 2015; Rathlev et al., 2018). If hospital leaders understand factors relating to LWT, they can mitigate the effects of overcrowding and long waits in the ER. Meeting the benchmark for LWT rates is an opportunity for hospital leaders to increase patient satisfaction and to allow their staff to provide quality care. DeFlitch, Geeting, and Paz (2015) indicated that bottlenecks create disparities between patients' needs and the ability to provide services. The ER staff should strive to provide the best care to patients and their families in emergency situations, with a goal to get every patient the desired outcome, without harm and waste of resources. The development of best practices and gold standards in emergency care will lead to process improvements and make positive contributions to public health.

Recommendations for Action

There are several recommendations for useful action that hospital leaders might employ to address the conclusions of this study and improve business practice. Hospital leaders, such as ER directors, and ER managers should pay attention to the study results and apply strategies to reduce LWT. Since ESI3 patients had the highest predictive power for LWT in this study, hospital leaders may consider re-designing patient flow to meet the needs of middle-acuity patients. In this study, it should concern hospital leaders that ESI2 was a more magnificent predictor of LWT than ESI5 because ESI2 patients are high-acuity and at-risk for rapid decompensation in their health status. ESI2 patients were the second most significant predictor of LWT in this study. The recommendations for hospital leaders to reduce LWT according to acuity level are (a) streaming, (b) split-flow, (c) physician-directed queueing, and (d) revised triage.

Streaming

Streaming is an evidence-based practice improvement strategy in the ER. One way that hospital leaders can mitigate the LWT rate for ESI3 patients is to implement streaming of ESI3 patients. Streaming is the smooth flow of patients as they enter, move through a system, and flow out, either to home or as a hospital admission (Morrish, 2012). The stream must not freeze, must remain free from large branches, rocks, or dams in order to maintain the flow for communities at the far end of the stream to rely on a sustainable stream for the present and the future (Morrish, 2012). Streaming is redirecting patients to the most appropriate care in the most appropriate setting.

England's National Health Service set a goal for all hospitals with an Accident and Emergency Department to expand to a front door streaming service by the end of October 2017, so that ER staff would have the ability to take care of the most urgent patients. Kmietowicz (2017) stated that the National Institute for Health Research was carrying out a study on the use of special accommodations for patients intoxicated from alcohol to ensure their safety while easing the pressure of ER staff. Iacobucci (2016) advised that having a more extensive array of health care professionals in the ER (general practitioners, psychiatrists, mental health or addiction specialists, and community pharmacists) would help make care more efficient and reduce ER overcrowding by using multiple professionals to stream patients arriving at the ER. The general practitioner could refer patients to primary health care, the ER, or another appropriate service setting for the chief complaint. Streaming may help drive efficiencies in ERs internationally.

Split-Flow

Split-flow allows the staff to split the ESI3 patients into horizontal and vertical categories (Bish et al., 2016). According to Bish et al. (2016), ESI4 and ESI5 patients go to a rapid care treatment area (e.g., fast-track), along with ESI3 patients that require fewer resources. Bish et al. considered ESI3 patients requiring fewer resources vertical when they only required brief treatment and were ambulatory, and did not require undressing for assessment. In this respect, ER bed space was for ESI patients that required more resources and needed to be horizontal in an ER bed. The suggestion for split-flow came from AHRQ, and Bish et al. (2016) and Christensen et al. (2016) studied split-flow as a strategy to reduce LWT. According to AHRQ (2014), horizontal patients go to the main ER because they have complaints that require more invasive testing and will most likely end up facing a hospital admission. Whereas, vertical patients, after assessment and treatment, will probably get discharged from the ER. ER providers should attempt to keep patients vertical, when appropriate, in an attempt to facilitate timely discharge (Christensen et al., 2016).

Physician-Directed Queueing

DeFlitch et al. (2015) expanded on the concepts of the provider in triage and split-flow in their PDQ model. PDQ means that the provider quickly evaluates all patients as they arrive. The provider handles patients that require few resources and directs more complex patients to the main ED for evaluation (DeFlitch et al., 2015). In the PDQ model, every patient receives an immediate provider evaluation, regardless of arrival mode and the provider orders the necessary testing, routing the patient to the appropriate queue for treatment. DeFlitch et al. also reviewed Press Ganey satisfaction surveys and found that patients had higher degrees of satisfaction when they did not have to repeat their clinical story to various care providers. The PDQ model allows for a fast acuity assessment to determine the ESI level so that the physician can equally distribute resources throughout the ER. As a result of the case study, Deflitch et al. were able to eliminate the waiting room entirely and nearly eradicate the LWT rate (5.7% at baseline and 0.6% 1-year post-PDQ).

Revised Triage

There are many methods of revised triage practices that promote quick triage of patients for classification into an ESI category. Christensen et al. (2016) studied the use of a pivot triage process in an ER. In their study, the pivot triage included only the necessary information to assign an acuity: Chief complaint, heart rate, oxygen saturation, and acuity level. The traditional triage contained chief complaint, full vital signs, medical history, surgical history, medication history, suicide screen, abuse screen, and acuity level. The faster triage process was an improvement in business practice because the patient could have a rapid assessment and immediately go to the most suitable treatment area. The study demonstrated that the patient was less likely to LWT from the waiting room if the nurse did a quick assessment, rather than having the patient wait for a prolonged period without any contact from a medical professional. Christensen et al. found a reduction in LWT from 2.6% before implementation of pivot triage to 1.0% after implementation of pivot triage.

Ashour and Kremer (2013) developed a triage algorithm using FAHP and MAUT to rank patients according to chief complaint, age, gender, pain level, and vital signs. Using DES, Ashour and Kremer compared the traditional ESI system with the FAHP-MAUT algorithm. Ashour and Kremer recommended the use of a FAHP-MAUT algorithm, which uses quantitative measures to assign a priority for each patient, rather than the ESI algorithm which relies on nursing judgments. The ESI is a nominal level of measuring patient acuity, and the nurse must place each patient into one category. There is no way to categorize the priority of patients within each category. Many hospitals do not allow ESI3 patients to have an evaluation in fast track (Soremekun et al., 2014). For this reason, ERs with fast tracks may have longer waits for ESI3 patients, and those without fast tracks may have longer waits for ESI4 and ESI5. Riordan, Dell, and Patrie (2016) derived and validated a model and designed a nomogram for ESI patients on arrival to predict discharge disposition that was especially helpful for appropriating ESI3 patients.

Recommendations for Further Research

There remains a gap in the ER literature to help hospital leaders use queueing principles in the ER to improve patient flow. The hospital queueing system as a whole has many inefficiencies that contribute to LWT, including lack of inpatient bed availability and other internal delays such as radiology and laboratory issues that cause bottlenecks. Future studies may focus on additional factors affecting throughput using queueing variables. This study only covers ER arrivals over a 6 month period, whereas years of historical data may provide more insight as to volume variability throughout the year, including specific days, seasons, and holidays. There were some limitations in this study that researchers could address in future studies. For example, the accuracy of archival data is subject to human error during entry into the electronic system. There are also limitations of the correlational research design. For example, a correlational researcher cannot determine causation for relationships between variables and is only able to predict a relationship between variables. To mitigate this limitation, researchers may want to find situations where it is possible to randomly assign participants to groups or to manipulate the study variables. DeFlitch et al., (2015) posited that there is a need for more research using engineering and systems-based solutions because previous strategies such as standing orders, split-flow models, waiting room management, and immediate bedding have not made drastic improvements in the system. Therefore, DeFlitch et al. recommended further study of operational methods in the ER, including queueing models and simulation.

Reflections

This doctoral journey taught me about the endless options for solving problems through research. I missed many events, family occasions, leisure with friends, and sacrificed many things in this pursuit. However, if I can affect any positive change as a result of this work, then the time I sacrificed with friends and family was not in vain. Since beginning the pursuit of this degree, I have lost people that I held dear to me, and the guilt of not seeing them more was overwhelming. However, I know that these loved ones would not have wanted me to do things any differently. I regret that they are not on this earth to hear that I finally finished this project and became Dr. Gibbs, but they would have been so proud of me. I want to encourage those who are still struggling through the doctoral process and wonder if the time, money, and effort spent are worthwhile. It is worth it; do not give up the fight. Take a break from the program if you need to, but do not let the program break you.

Conclusion

ER crowding is a significant problem in healthcare leading to poor quality of care and patients not having access to care. It is necessary to recognize bottlenecks in the ER and create new methods to increase patient flow. The take-home message for readers of this study is that patients are more likely to leave if they have to wait. The fundamental reason for QT research is to find out what delays influence waiting and to make every effort to eliminate those delays. One might conclude from this study that patients of specific acuity levels have certain expectations of how long they will wait for treatment. Hospital leaders have no way of knowing the outcomes for patients that LWT, including permanent preventable disability or even mortality.

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Appendix A

LIST OF A. K. ERLANG'S PUBLICATIONS IN CHRONOLOGICAL ORDER

SURVEY p.

Appendix I of a Lecture by G. F. O'Dell: The Influence of Traffic on Automatic Exchange Design.
The Institution of Post Office Electrical Engineers, Publication No. 85, London, 1920 106

Sandsynlighedsregningens Anvendelse i Telefondrift.
Første Nordiske Elektroteknikermøde i København 1920 (H. C. Ørstedsmødet), Copenhagen, 1922, p. 149, and in: Elektroteknikeren *19* (1923) 99 104

Solutions de quelques problèmes de la théorie des probabilités présentant de l'importance pour les bureaux téléphoniques automatiques.
Annales des Postes, Télégraphes et Téléphones *11* (1922) 800 102

Review of "Karl Pearson: Tables of the Incomplete Gamma-Function".
Skandinavisk Aktuarietidsskrift *6* (1923) 128 111

Et Bevis for Maxwells Lov, Hovedsætningen i den kinetiske Luftteori.
Fysisk Tidsskrift *23* (1925) 40 108

Some Applications of the Method of Statistical Equilibrium in the Theory of Probabilities.
Den sjette Skandinaviske Matematikerkongres i København 1925, Copenhagen, 1926, p. 157 105

Application du calcul des probabilités en téléphonie.
Annales des Postes, Télégraphes et Téléphones, *14* (1925) 617 104

Calcul des probabilités et conversations téléphoniques.
Revue générale de l'Electricité *18* (1925) 305 101

Calcul des probabilités et conversations téléphoniques.
Revue générale de l'Electricité *20* (1926) 270 103

Démonstrations de la Loi de Maxwell, proposition fondamentale de la théorie des gaz.
La Vie Technique et Industrielle *8* (1926) 72 108

Om et Par nye Multiplikationstabeller; en udvidet Anmeldelse.
Matematisk Tidsskrift A, *38* (1927) 115 111

Etude théorique élémentaire sur le transformateur d'un appareil téléphonique.
La Vie Technique et Industrielle *9* (1927) octobre 128

Quelques applications de la méthode de l'équilibre statistique dans la théorie des probabilités.
Annales des Postes, Télégraphes et Téléphones *17* (1928) 743 105

Femcifrede Logaritmer og Antilogaritmer. — Five Figure Tables of Logarithms and Anti-Logarithms.
Edited by R. E. H. Rasmussen, Copenhagen, 1930 110

On the Rational Determination of the Number of Circuits.
Written 1924. Published in the present book as no. 6, p. 216 106

Principal Works of A. K. Erlang.
Published in the present book as nos. 1—11, see Contents, p. 5.

Brockmeyer, E., Halström, H. L., & Jensen, A. (1948). *The life and works of A. K. Erlang (Transactions of the Danish Academy of Technical Sciences 1948, no. 2).* Copenhagen, Denmark: Akademiet for de Tekniske Videnskaber.

Appendix B: Confidentiality Agreement

Name of Signer: Joy Gibbs

I am aware that I will have access to information which is confidential while collecting data for this research: "Queueing Variables and Left without Treatment Rates in the Emergency Department." I acknowledge that the information must remain confidential, and that improper disclosure of confidential information can be damaging to the hospital.

By signing this Confidentiality Agreement, I acknowledge and agree that:

1. I will not disclose or discuss any confidential information with others, including friends or family.
2. I will not in any way divulge, copy, release, sell, loan, alter or destroy any confidential information without authorization from hospital administration.
3. I will not discuss confidential information where others can overhear the conversation. I understand that it is not acceptable to discuss confidential data even if I do not use the name of the hospital.
4. I will not make any unauthorized transmissions, inquiries, modification or purging of confidential information.
5. I agree that my obligations under this agreement will continue after termination of the job that I will perform.
6. I understand that violation of this agreement will have legal implications.
7. I will only access or use systems or devices I am officially authorized to access, and I will not demonstrate the operation or function of systems or devices to unauthorized individuals.

Signing this document, I acknowledge that I have read the agreement and I agree to comply with all the terms and conditions stated above.

Signature: **Date:**

Appendix C: Data Use Agreement

This Data Use Agreement ("Agreement"), effective as of March 16, 2018, is entered into by and between Joy Gibbs ("Data Recipient") and [redacted] ("Data Provider"). The purpose of this Agreement is to provide Data Recipient with access to a Limited Data Set ("LDS") for use in research in accord with the HIPAA and FERPA Regulations.

Definitions. Unless otherwise specified in this Agreement, all capitalized terms used in this Agreement not otherwise defined have the meaning established for purposes of the "HIPAA Regulations" codified at Title 45 parts 160 through 164 of the United States Code of Federal Regulations, as amended from time to time.

Preparation of the LDS. Data Provider shall prepare and furnish to Data Recipient a LDS in accord with any applicable HIPAA or FERPA Regulations

Data Fields in the LDS.

No direct identifiers such as names may be included in the Limited Data Set (LDS). The researcher will also not name the organization in the doctoral project report that is published in Proquest. In preparing the LDS, Data Provider or designee shall include the **data fields specified as follows**, which are the minimum necessary to accomplish the research: approximately 5 months of **daily** data (October 1, 2017, through February 28, 2018) for the Emergency Department (ED):

- Arrivals to the ED;
- Left Without Treatment (LWT) rate;
- Average time until triage;
- Rooming times;
- Medical Screening Evaluation (MSE) time;
- The number of patients that LWT for each Emergency Severity Index (ESI) Level, including patients that have not yet been assigned an ESI Level when they LWT, and
- The number of nurses, midlevel practitioners, doctors, and technicians (direct care staff) on for each 24-hour period.

Responsibilities of Data Recipient. Data Recipient agrees to:

Use or disclose the LDS only as permitted by this Agreement or as required by law;

Use appropriate safeguards to prevent use or disclosure of the LDS other than as permitted by this Agreement or required by law;

Report to Data Provider any unintentional use or disclosure of the LDS of that I find is not allowed by this Agreement or required by law;

Require any of its subcontractors or agents that receive or have access to the LDS to agree to the same restrictions and conditions on the use and disclosure of the LDS that apply to Data Recipient under this Agreement; and

Not use the information in the LDS to identify or contact the participating hospital.

Permitted Uses and Disclosures of the LDS. Data Recipient may use and disclose the LDS for its research activities only.

Term and Termination.

Term. The term of this Agreement shall commence as of the Effective Date and shall continue for so long as Data Recipient retains the LDS, unless sooner terminated as outlined in this Agreement.

Termination by Data Recipient. Data Recipient may terminate this agreement at any time by notifying the Data Provider and returning or destroying the LDS.

Termination by Data Provider. Data Provider may terminate this agreement at any time by providing thirty (30) days prior written notice to Data Recipient.

For Breach. Data Provider shall provide written notice to Data Recipient within ten (10) days of any determination that Data Recipient has breached a material term of this Agreement. Data Provider shall afford Data Recipient an opportunity to cure said alleged material breach upon mutually agreeable terms. Failure to agree on mutually agreeable terms for cure within thirty (30) days shall be grounds for the immediate termination of this Agreement by Data Provider.

Effect of Termination. Sections 1, 4, 5, 6(e) and 7 of this Agreement shall survive any termination of this Agreement under subsections c or d.

Miscellaneous.

Change in Law. The parties agree to negotiate in good faith to amend this Agreement to comport with changes in federal law that materially alter either or both parties' obligations under this Agreement. Provided, however, that if the parties are unable to agree to mutually acceptable amendment(s) by the compliance date of the change in applicable law or regulations, either Party may terminate this Agreement as provided in section 6.

Construction of Terms. The terms of this Agreement shall be construed to give effect to applicable federal interpretative guidance regarding the HIPAA Regulations.

No Third Party Beneficiaries. Nothing in this Agreement shall confer upon any person other than the parties and their respective successors or assigns, any rights, remedies, obligations, or liabilities whatsoever.

Counterparts. This Agreement may be executed in one or more counterparts, each of which shall be deemed an original, but all of which together shall constitute the same instrument.

Headings. The headings and other captions in this Agreement are for convenience and reference only and shall not be used in interpreting, construing or enforcing any of the provisions of this Agreement.

IN WITNESS WHEREOF, each of the undersigned has caused this Agreement to be duly executed in its name and on its behalf.

DATA PROVIDER	**DATA RECIPIENT**
Signed: ________________________	Signed: ________________________
Print Name: ____________________	Print Name: ____________________
Print Title: _____________________	Print Title: _____________________