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# Organizational Factors of Emergency Room Fast-Track Admission Duplicate Data Entry Errors in an Alabama Health System

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This is to certify that the doctoral dissertation by

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

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MPhil, Walden University, 2020

MBA, University of Phoenix, 2012

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Dissertation Submitted in Partial Fulfillment

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Abstract

Inaccurate patient information resulting from duplicate record data entry errors can compromise patient safety. Emergency room (ER) visits in the United States have increased by 15% over the last decade, and the increase has prompted hospitals to implement fast-track admissions in the ER to mitigate overcrowding and expedite the admission process for patients with low-acuity symptoms. Although duplicate record data entry errors occur frequently in ER admissions, there is a lack of information about fast-track ER admissions and the predictors of different types of confirmed duplicate record data entry errors. This correlational quantitative study examined the associations between work shift (four staggered shifts over 24 hours between 5:00 a.m. and 5:00 a.m.), number of daily ER admissions, and number of duplicate record data entry errors (misspelling of first and last name and transposed social security number [SSN]) from 19 months of admissions at two acute care hospitals in an Alabama health care system using the human error theory as a foundation and retrospective secondary data from March 2019 to September 2020. Kruskal-Wallis H test, chi-square test of independence, and linear regression analyses were used. The results showed statistically significant associations between work shift, number of daily ER fast-track admissions, and number of duplicate record data entry errors (name and SSN). Implications for positive social change include informing ER leaders about predictors of duplicate record data entry errors which can improve the quality of fast-track patient admissions and patient safety.

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# Dedication

This dissertation is dedicated to my family. To my husband, Kenyata, thank you for your support and understanding of the time needed to complete my research. Thank you for your encouraging words to keep me going when I was discouraged and wanted to give up. To my son, KJ, I hope that I can be an example for you to keep going after your dreams no matter how tough it becomes. To my parents and brother, thank you for your continued support in my ambitions and keeping me uplifted in prayer.

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# Chapter 1: Introduction to the Study

ER dynamics produce challenging demands for ER workers in robust hospital departments (Weigl et al., 2016). Fast-track admissions represent one dynamic of ER functions (Gasperini et al., 2020). This type of admission allows patients to bypass the patient registration desk and go to triage. Once they complete triage, they move to an exam room where a physician sees them. The patient registrar then completes registration at the bedside using a mobile computer (Alishahi Tabriz et al., 2020; Gasperini et al., 2020). ER visits increased by 15% between 2009 and 2019, from 120 million to 138 million visits (Quattrini & Swan, 2019). This increase prompted health care leaders to implement fast-track ER admissions to mitigate overcrowding and expedite the admissions process for patients with low-acuity symptoms (Flynn et al., 2017; Quattrini & Swan, 2019).

Fast-track admission in the ER requires patient registration, which involves the collection of demographic information such as first and last name, address, date of birth (DOB), and social security number (SSN). Intake personnel must accurately identify patients, or patient misidentification will occur and result in duplicate record data entry errors, such as misspelling of first and last name or address, incorrect DOB, and transposed SSN. Additionally, duplicate records may compromise patient safety and quality of care (American Health Information Management Work Group, 2016).

The current study was designed to raise awareness of duplicate record data entry errors in the ER among health information and ER managers. Managers may also become aware of variables, such as work shift and the number of daily ER admissions, as possible contributors to duplicate record data entry errors during fast-track admissions. Policies and procedures for capturing accurate data and patient verification may need to be modified. These implications may improve data integrity in ERs. The following sections provide information about the background, problem, purpose, and research questions in this study.

## Background

Health care organizations across the United States struggle with duplicate record data entry errors. Duplicate medical record rates ranged from 5% to 10% for freestanding facilities and larger health systems consisting of multiple hospitals and clinics ranged up to 20% (Harris & Houser, 2018). Previous researchers asserted that the root cause of duplicate medical records is individual user and system error, limited functionality, or other software issues (Khunlertkit et al., 2021). Other duplicate record causes include poor working conditions, lack of support from colleagues and administrators, and inadequate training (Khunlertkit & Paine, 2015). Landsbach (2016) showed data entry errors occur more often in the ER than in other areas of the hospital, with 62% of hospital errors occurring in this department. Landsbach (2016) reported that the other 38% of errors occurred in departments such as radiology, lab, labor and delivery, and oncology.

Data entry errors such as misspelling of first and last name or address, incorrect DOB, and transposed SSN occur because patient registrars can transpose numbers or letters while entering patient information, which causes duplicate records if the patient registrar cannot locate a patient's existing record created during a previous admission (Harris & Houser, 2018). The patient registration process should first consist of patient verification, such as reviewing a driver's license and searching for the patient in the master patient index (MPI) using first and last name and DOB (Harris & Houser, 2018). If the patient does not populate in the system, the registrar should verify the patient's information is correct before creating a new record (Harris & Houser, 2018). Registrars may not always follow the verification process, causing duplicate record data entry errors (Leventhal & Schreyer, 2020; Prints et al., 2020).

Previous literature suggested patient registrars contributed to ER duplicate record data entry errors (Landsbach, 2016); however, no literature or research existed on variables such as work shift and the number of daily ER admissions as possible contributors to duplicate record data entry errors during fast-track admissions in the ER. ER leaders implemented fast-track admissions in the ER to mitigate overcrowding and expedite the admission process for patients with low-acuity symptoms after ER visits, which increased by 15% between 2009 and 2019 from 120 million to 138 million visits (Flynn et al., 2017; Quattrini & Swan, 2019).

Fast-track admissions allow patients to bypass the registration desk (Gasperini et al., 2020). After completing triage, patients move to an exam room to see the physician. The patient registrar then completes registration at the patient's bedside before the physician sees the patient (Alishahi Tabriz et al., 2020; Gasperini et al., 2020). I determined a need existed to learn more about the number of duplicate record data entry errors created during fast-track admissions in the ER and to assess whether variables such as work shift and number of daily admissions contribute to the errors.

## Problem Statement

The patient registration department in the ER must accurately identify patients and enter patient demographic information into the hospital's MPI because this interaction represents the patient's first encounter with the health care facility. The ER patient registration department creates up to 62% of the duplicate record errors in health care organizations (Landsbach, 2016). Patient misidentification and the creation of duplicate records could result in compromised patient safety and quality of care for the duration of the patient's stay in a health care facility (Banton & Filer, 2014). Furthermore, duplicate records negatively impact a health care organization's business performance, with some hospitals losing more than $40 million in revenue over the course of a year (Banton & Filer, 2014).

The ER's fast-paced environment can result in errors such as misspelling of first and last name or address, incorrect DOB, and transposed SSN. These errors lead to the creation of duplicate records that transfer to health care applications such as electronic health records (EHRs), pharmacy record systems, and patient registries. Duplication in these systems can compromise patient safety and quality of care (Banton & Filer, 2014; Cohen et al., 2019). Duplicate records can result in unnecessary medical procedures, reimbursement issues for both payer and provider, and potential malpractice claims (Zhao, 2018). Although previous researchers showed that duplicate record data entry errors remain a problem in ER patient registration departments, no existing studies showed how duplicate record data entry errors were created during fast-track ER admissions and whether variables such as work shift and number of daily admissions contributed to the errors. Work shift may contribute to the number of duplicate record data entry errors during fast-track ER admissions because the number of patients admitted during a certain time could result in a heavy caseload, thereby causing errors (Leventhal & Schreyer, 2020).

## Purpose of the Study

The purpose of this correlational quantitative study was to examine the associations between work shift, number of daily ER admissions, and number of duplicate record data entry errors (i.e., misspelling of first and last name or address, incorrect DOB, and transposed SSN) at two acute care hospitals in an Alabama health care system.

## Research Questions and Hypotheses

The first two research questions (RQs) for this study guided an examination of the associations between the independent variables (work shift and number of daily ER admissions) and the dependent variable (number of duplicate record data entry errors that included misspelling of first and last name or address, incorrect DOB, and transposed SSN) in the ER. In RQ3, I combined the independent variables to test for all possible associations with the number of duplicate record data entry errors. The following RQs and hypotheses guided this study:

RQ1: What is the association between the work shift and the number of duplicate record data entry errors for fast-track ER admissions?

$H_0$1: There is no association between the work shift and the number of duplicate record data entry errors for fast-track ER admissions while controlling for the number of daily ER admissions.

$H_a$1: There is an association between the work shift and the number of duplicate record data entry errors for fast-track ER admissions while controlling for the number of daily ER admissions.

RQ2: What is the association between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions?

$H_0$2: There is no association between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions.

$H_a$2: There is an association between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions.

RQ3: What is the association between the work shift, the number of daily ER admissions, and the number of duplicate record data entry errors for fast-track ER admissions?

$H_0$3: There is no association between the work shift, the number of daily ER admissions, and the number of duplicate record data entry errors for fast-track ER admissions.

$H_a$3: There is an association between the work shift, the number of daily ER admissions, and the number of duplicate record data entry errors for fast-track ER admissions.

## Theoretical Framework

Reason (2000) formulated the human error theory, which encompasses two approaches: person and system. In the person approach, Reason blamed the harmful errors of health care professionals on mental processes and moral instability. In the system approach, Reason expected human error to occur in all health care organizations. Reason explained that theorists using the systems approach do not focus on the individual but on how individuals work and the root causes of why an error occurs. I determined the system approach of the human error theory was most appropriate for this study because I planned to examine the number of duplicate record data entry errors made during fast-track admissions in the ER, with a focus on possible contributors to the errors, such as work shift and number of daily ER admissions.

The human error theory aligned with this study because it is best used in a health care environment and can enable the researcher to relate to various types of health care errors within a health care organization. Human error theory's system approach provided the best foundation for this study because I planned to evaluate the independent variables of work shift and the number of daily ER admissions in the context of the dependent variables of number of duplicate record data entry errors occurring during fast-track admissions in the ER. The system approach facilitates the evaluation of the system processes that may cause human error, enabling researchers to alert organizational leaders when system issues could be addressed to mitigate errors. Chapter 2 provides more information about human error theory and its role in this study.

## Nature of the Study

This was a quantitative correlational study. In correlational studies, researchers focus on the relationships between variables (Wilson & Joye, 2017). In this study, I examined the relationships between work shift and number of daily ER admissions (independent variables) and the number of duplicate record data entry errors (dependent variable). I analyzed the duplicate medical record report consisting of potential duplicate record data entry errors from fast-track admissions for both hospitals. These errors included misspelling of first and last names and transposed SSNs from March 2019 to September 2020. The duplicate medical record report alerts the health information management (HIM) director of potential duplicate records, and HIM staff must confirm the existence of true duplicates by completing a manual verification process consisting of name, address, insurance, signature, and SSN verification from various software applications. The HIM director assisted with obtaining the duplicate report; however, a duplicate report was created for this study because many of the elements that were needed for data analysis are not included in the duplicate report generated from the EHR (Paragon) used on a daily basis. The staff members identified and confirmed the data entry errors that caused the initial duplicate record for each duplicate pair. The HIM director de-identified the report of all protected health information (PHI) before releasing it to me. The HIM director replaced PHI in the duplicate record pairs with the numerical designations Record 1 and Record 2. I counted all data entry errors from confirmed duplicates. I accessed the number of daily fast-track admissions using a separate report and analyzed for the number of ER admissions per day during each work shift (i.e., four staggered shifts over 24 hours between 5:00 a.m. and 5:00 a.m.). I measured the work shift based on the time of admission in the ER for each patient record on the report.

I signed a business associate agreement and a data agreement with the health system in Alabama, in which the health system granted permission for me to receive duplicate patient records from both hospitals. I organized data into IBM's Statistical Package for the Social Sciences (SPSS) software and analyzed the data using chi-square test of independence, Kruskal-Wallis H Test, and simple and multiple linear regression.

## Definitions

*Confirmed duplicates*: Confirmed (i.e., true) duplicates are duplicate record pairs on the facility duplicate report that have been manually verified by HIM staff as the same patient (Crew et al., 2020).

*Duplicate record data entry errors*: Duplicate record data entry errors consist of misspelling of first and last names or addresses, incorrect DOBs, and transposed SSNs between two records. Duplicate record data entry errors occur when personnel do not properly identify patients at the point of admission or inaccurately capture their personal information (Khunlertkit et al., 2021).

*Fast-track admissions*: Fast-track admissions allow patients to bypass the registration desk to be triaged and immediately taken to a room for treatment and bedside registration in the ER (Gasperini et al., 2020). Flynn et al. (2017) asserted that some variations of the fast-track process in the ER allow paramedics and nurses to assist with the registration process in addition to triage. Flynn et al. (2017) explained that fast-track admissions were developed to mitigate overcrowding and extensive ER wait times.

*Health information management (HIM)*: HIM refers to the practice of managing patient information and maintaining patient privacy and security (Lintz, 2018).

*Master patient index (MPI)*: The MPI is a health care software application that houses patient demographic information such as name, address, DOB, SSN, and insurance information. Additionally, personnel capture patient encounter information specific to the health care organization into the MPI and specify the type of encounter, such as inpatient or outpatient. Personnel also capture dates of service and financial information, such as itemized billing (Zhao, 2018).

*Number of daily ER admissions*: The number of daily ER admissions served as an independent variable in the study and represented the number of patients admitted to the ER each day (i.e., four staggered shifts over 24 hours between 5:00 a.m. and 5:00 a.m.). I obtained the number of patients admitted to the ER from a separate report with the combined total of admissions for both hospitals. I determined the number of ER admissions per day in SPSS using the admissions and duplicate record report. I combined the number of daily ER admissions because HIM reporting for the health system combines both hospitals. Both ERs fast-tracked all patients; therefore, the number of daily admissions included all fast-track patients.

*Patient registrar*: Patient registrars serve as data entry staff located in various departments of the hospital. They must capture accurate patient identification upon their arrival. Patient registrars should conduct a verification process when identifying the patient and use several search techniques when searching for the patient in the MPI (e.g., first and last name and DOB) before creating a new record to avoid duplicate record data entry errors. Patient registrars should receive ongoing training and support to ensure they maintain the data integrity of the MPI and other health care applications (Biddle, 2015).

*Potential duplicates*: Potential duplicates refer to duplicate pairs that have been identified on the facility duplicate report pulled from Paragon but are not yet confirmed. Personnel must perform manual verification of patient information using first and last name, DOB, SSN, insurance, and signatures to confirm whether the duplicate pair is a true duplicate.

*Work shift*: Work shift served as an independent variable in the study. Patient registrars worked four staggered shifts in the 24 hours between 5:00 a.m. and 5:00 a.m. in the two Alabama hospital ERs. I determined work shift using time-of-day patient ER admittance indicated on the duplicate report.

## Assumptions

There were two assumptions associated with the study. I assumed that the data provided on the duplicate report was accurate. The HIM staff manually determined whether each duplicate pair on the report was a true duplicate by using software applications to verify patient demographics (e.g., first and last name, DOB, SSN, insurance, and signatures). This created additional work for employees because the report was created for the study, and the work involved to confirm the duplicates on the report was in addition to their daily tasks. Further, the employees had to meet a deadline for completing the report. To provide reassurance of time, I communicated to the employee and HIM director that I would provide a deadline for completing the report. Secondly, I assumed I would be able to obtain a minimum sample size from the duplicate report. I used 19 months of data, and 20–30 duplicates were confirmed per month, so I estimated I would receive 420–630 samples, which would meet the minimum sample size requirement of 302 for the study.

## Scope and Delimitations

The scope of the study was limited to the number of duplicate record data entry errors in two Alabama hospital ERs. The duplicate report also contained duplicate record data entry errors from inpatients admitted to other floors within the hospitals, but my focus was on data entry errors for ER admissions because 62% of duplicate record data entry errors occur in the ER (Landsbach, 2016). Duplicate record data entry errors represent the most common data entry errors made during patient registration in the ER (Landsbach, 2016); therefore, I did not consider other data entry errors, such as multiples or overlays, for this study. Multiples are identified when patients are added to an MPI more than twice resulting in multiple medical record numbers (Biddle, 2015). Overlays are the result of two patients sharing a medical record number in addition to intermingled records (Biddle, 2015). The scope of the study was also limited by my consideration of the number of daily ER admissions and work shift as possible contributors to the number of duplicate record data entry errors reported. I did not include the patient registrar employee responsible for registering the patient in the scope because the system model of the human error theory guiding this study dictated focusing on potential process failures (e.g., work conditions that may contribute to human error) instead of the individual (see Reason, 2000). I measured the work shift in which the error occurred by using the time the patient was admitted to the ER. I anticipated this would help me determine whether work shift contributed to the number of duplicate record data entry errors created during fast-track ER admissions.

## Limitations

Data collection presented a limitation in the study because it was limited to the duplicate report provided by the health care facility. The HIM department pulls the report from the EHR (Paragon) and uses this daily to review potential duplicate record data entry errors created at the point of registration and to manually confirm whether those errors are true duplicates. The duplicate report is currently the only method the HIM department uses to identify and correct duplicate records. Additionally, the duplicate report was limited to the specific types of data that were displayed; therefore, limited variables existed for testing and analysis of possible contributors to the creation of duplicate record data entry errors during fast-track ER admissions. This may have skewed the results by not fully revealing all possible contributors and associations. Additionally, the two Alabama hospitals fast-track all patients who arrive in the ER, limiting this data set to only fast-track admissions. Findings can be generalized to other hospitals where ERs use a fast-track process. Furthermore, the use of one health system within the state of Alabama may also have limited the study results.

## Significance

The MPI serves as the gatekeeper of patient information within health care organizations. Health care workers rely on the MPI for accuracy of the information to successfully perform treatment, billing, and operations (Zhao, 2018). Minimizing duplicate record data entry errors such as misspelling of first and last names or addresses, incorrect DOBs, and transposed SSNs will allow health care organizations to maintain data integrity within their health care applications and efficiently enter accurate information upon patient admission to the ER. Additionally, providers will be able to provide adequate patient care by having a complete and accurate patient record to reference (Zhao, 2018). The positive social change implications from this study included mitigation strategies and revised policies and procedures based on possible contributors (e.g., work shift and number of daily ER admissions) to the number of duplicate record data entry errors.

## Summary

The ER remains a challenging environment in which duplicate record data entry errors occur during the fast-track admissions process (Leventhal & Schreyer, 2020). Duplicate record data entry errors consist of misspelling of first and last names or addresses, incorrect DOBs, and transposed SSNs. Fast-track admissions provide an expedited admissions method that allows patients to be immediately triaged and taken to an exam room for treatment and bedside registration (Gasperini et al., 2020). Additionally, ER managers implemented fast-track admissions in the ER to mitigate overcrowding and expedite the admission process for patients with low-acuity symptoms (Flynn et al., 2017; Quattrini & Swan, 2019).

I collected and analyzed data from both hospitals' duplicate reports; however, the duplicate report was limited to potential duplicate records created during fast-track admissions and manually confirmed to be true duplicates. Human error theory served as the study's foundation, providing a system approach focused on the work conditions of the individual and the root causes of the errors (see Reason, 2000). Duplicate record data entry errors occurred at two acute Alabama hospital ERs where I conducted this correlational quantitative study to examine the associations between the number of duplicate record data entry error types (e.g., misspelling of first and last names and transposed SSNs), work shift (four staggered shifts over a 24-hour period), and the number of daily admissions in the ER. Chapter 2 presents the literature review.

# Chapter 2: Literature Review

The problem addressed in this study involved the duplicate record data entry errors occurring during fast-track ER admissions. Duplicate record data entry errors have become a major issue across the health continuum and have resulted in an identification crisis across the United States (Lippi et al., 2017). The rates for duplicate medical records range from 5% to 10% for most freestanding facilities (Harris & Houser, 2018). Larger health systems consisting of multiple hospitals and clinics have rates up to 20% (Harris & Houser, 2018). Duplicate record data entry errors appear in demographic data and consist of misspelling of first and last names or addresses, incorrect DOBs, and transposed SSNs. Patient registrars create duplicate record data entry errors when they cannot locate a patient's existing medical record.

Duplicate records create two sets of medical records for a patient (Cohen et al., 2019). Duplicate record data entry errors impact a patient's quality of care, resulting in medical errors such as incorrect or missed treatments, reviewing incorrect medical records, or misidentifying a patient (Lippi et al., 2017). The Joint Commission identified that 10.6% of medical errors occur because of duplicate record data entry errors (Lippi et al., 2017). Furthermore, duplicate record data entry errors can negatively impact the financial health of health care organizations by leading to claim denials that decrease revenue (Petaschnick, 2017).

ER managers implemented fast-track admissions to mitigate overcrowding and expedite the admission process for patients with low-acuity symptoms after ER visits, which increased by 15% between 2009 and 2019 (Flynn et al., 2017; Quattrini & Swan, 2019). In fast-track admissions, patients undergo an expedited registration process that consists of bypassing the patient registration desk and going to triage (Gasperini et al., 2020). Once triaged, patients move to an exam room to see the physician. Personnel then complete registration at the bedside (Alishahi Tabriz et al., in press; Gasperini et al., 2020). Fast-track admissions allow the patient to be treated and discharged from the ER at a faster rate, decreasing the length of stay and improving the quality of care (Gasperini et al., 2020; Rogers et al., 2017). The purpose of this correlational quantitative study was to examine the associations between work shift, number of daily ER admissions, and number of duplicate record data entry errors (i.e., misspelling of first and last name or address, incorrect DOB, and transposed SSN) at two acute care hospitals in an Alabama health care system. Chapter 2 includes the literature search strategy, a discussion of Reason's human error theory, and a review of literature related to duplicate record data entry errors, ER fast-track admissions, work shift, and number of daily ER admissions. The chapter also provides a discussion of the justification of the literature selected for the review.

## Literature Search Strategy

To conduct the literature review, I accessed the following library databases from the Walden University Library: Science Direct, CINAHL and MEDLINE combined search, CINAHL Plus with full text, ProQuest, and Thoreau multi-database search. Databases accessed outside of the Walden University Library included Google Scholar and American Health Information Management Body of Knowledge. Key search terms included the following: *duplicate medical records*, *data integrity*, *patient registration*, *emergency room*, *emergency department*, *data entry errors*, *electronic health records*, *electronic medical records*, *fast-track admissions*, and *paramedics*. Combinations of search terms included *duplicate medical records* and *patient registration*; *data entry errors* and *data integrity*; *data entry errors* and *electronic health records* or *electronic medical records*; *emergency room* and *paramedics*; *emergency room* and *fast-track admissions*; and *patient registration*; *emergency room*, *data entry errors*, *data integrity*, and *electronic health records* or *electronic medical records*; and *emergency room data entry errors*.

The scope of literature included publications dated from 2013 to 2022 to provide the most current information for the study. I reviewed older studies to establish foundational knowledge of fast-track admissions and duplicate record data entry errors. Additionally, some studies involved populations outside of the United States. Fast-track admission processes in the ERs of these international organizations were comparable to those in the United States, and the organizations also experienced similar issues with duplicate record data entry errors. The types of literature and sources searched included peer-reviewed research, dissertations, and journal periodicals.

## Theoretical Foundation

Human error theory, formulated by Reason (2000), provided the theoretical foundation for this study. The following sections provide a discussion of the elements of human error theory, including the person, system, and Swiss cheese models and how the models were used in previous research. The sections also provide discussions of the rationale for use in the current study.

### Person and System Models

Reason (2000) explained that the human error theory includes the person and system models. Reason asserted that the person model emphasizes the health care worker and the harmful errors created by their forgetfulness, inattention, poor motivation, carelessness, negligence, and recklessness. Reason explained that the mitigating errors occurring within the person approach involve mostly blaming, shaming, and threatening, and added that system model subscribers expect human error regardless of the organization type. Reason contended that according to the system model, errors will occur; however, organizational leaders should evaluate system processes and working conditions based on the specific type of error.

### Swiss Cheese Model

Reason (2000) used the Swiss cheese model as an analogy to describe system errors in health care organizations. Ideally, systems or organizations should have defense layers to protect data from errors created by people, technology, policies, and procedures; however, the layers have holes, like a slice of Swiss cheese. Holes develop based on active failures or latent conditions and are not necessarily a cause for concern until the holes align to present an opportunity for adverse events (Larouzee & Le Coze, 2020). Active failures include specific acts by an individual who has direct contact with the system or patient that result in a variety of errors, such as slips, lapses, fumbles, mistakes, and procedural violations. Additionally, active failures are short-lived once the cause has been identified, and health care administrators do not evaluate other organizational factors that may have contributed to them (Larouzee & Le Coze, 2020). Strategic planning by executives, in addition to organizational factors such as staffing, individual experience, pressure to complete tasks in a timely manner, or inadequate and outdated hardware and software applications, all lead to latent conditions. Latent conditions can cause a hole in the system or organization; however, health care administrators will not recognize latent conditions as a possible threat or contributor to errors until an adverse event occurs. Therefore, the latent conditions can remain dormant until processes are evaluated and modified. Latent conditions will increase and pose safety threats if organizational leaders do not rectify them (Larouzee & Le Coze, 2020).

**Analysis of Human Error Theory in Other Research**

Other researchers have used human error theory. Watson (2016) explained that in one outpatient clinic, office staff captured incorrect patient demographics and surgery information through verbal conversation or electronic capture. Watson also described clinic personnel not following a standard process, resulting in errors and in wrong-site surgery. Watson applied the system model of the human error theory because the surgery scheduling errors were linked to system errors, such as the staff not having adequate training and the lack of proper procedures. Watson identified staff members' failure to obtain critical patient information as active failures because these errors resulted in adverse consequences for the patients. Additionally, Watson determined that scheduling surgeries verbally by phone represented a latent condition because this organizational process had proved ineffective and in need of modification by the administration.

Similarly, Burns (2017) studied adverse medical errors using human error theory as the theoretical foundation. Burns aimed to evaluate the application of the human factors analysis and classification system to identify the human and systemic factors of medical errors at a health care organization. Burns used the Swiss cheese model to ground the use of the human factors analysis and classification system. Burns identified unsafe acts, a level of events grouped within the human factors analysis and classification system, as active failures. Preconditions for unsafe acts, unsafe supervision, and organizational influences represented the next levels Burns identified as latent conditions. Burns claimed that events resulting in harm occurred more often than others and asserted the prevalence of system factors in causing medical errors over individual errors. Burns concluded that system factors should be the focus of efforts to minimize medical errors in the health care organization.

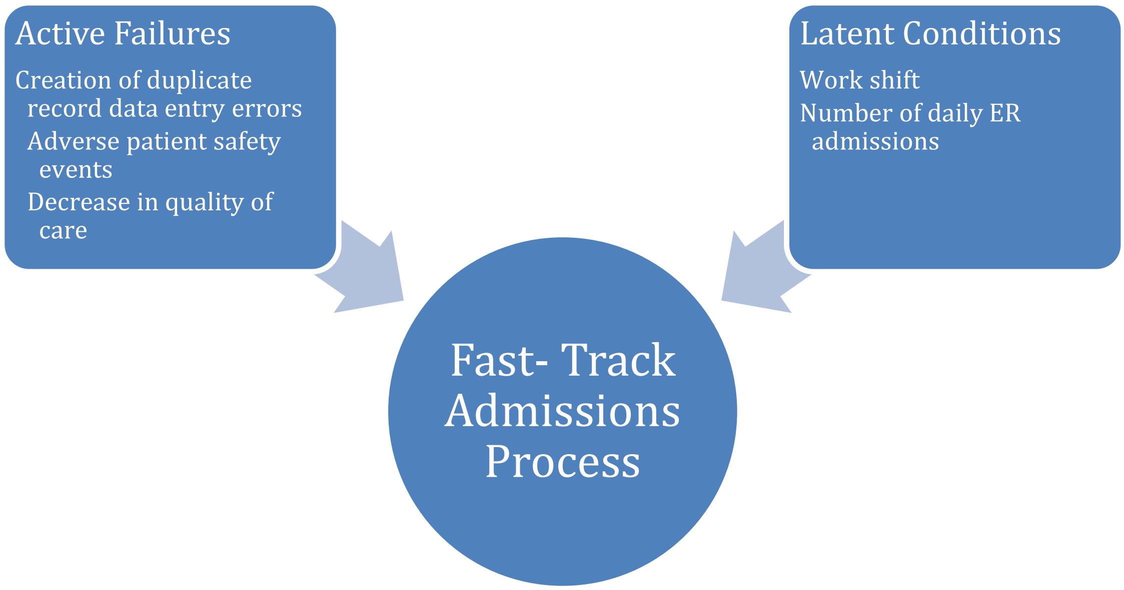
**Rationale for Use in Study**

The human error theory aligned with this study because it is best used in a health care environment and can be applied to various types of health care errors within a health care organization. The system approach of human error theory provided the best foundation for this study because I evaluated the independent variables (work shift and number of daily ER admissions) and the dependent variable (number of duplicate record data entry errors) occurring during fast-track admissions in the ER. The system approach of the human error theory enables the evaluation of system processes that may cause human error, creating an ability to alert organizational leaders of existing system issues in need of mitigation (Reason, 2000).

The Swiss cheese model also applied to this study because I aimed to investigate whether work shift and number of daily ER admissions contributed to duplicate record data entry errors. The creation of duplicate record data entry errors, which can result in adverse patient safety events and a decrease in the quality of care, represented active failures that could be resolved at the front end. The impact of work shift and the number of ER daily admissions on the creation of duplicate record data entry errors represented possible latent failures in the fast-track ER admissions process. These latent conditions could remain dormant if left unexamined by health care administrators who do not consider work shift and number of daily admissions as organizational factors that could contribute to the number of duplicate record data entry errors occurring during fast-track ER admissions. Latent conditions should alert health care administrators to a problem so they can develop mitigation and resolution strategies (Larouzee & Le Coze, 2020). Figure 1 shows how I applied the Swiss cheese model to this study.

**Figure 1**

*Use of Reason's Swiss Cheese Model in Current Study*




**Use of Theory in Current Study**

The systems approach outlined in human error theory grounded this study. This approach facilitates a focus on organizational factors, such as workload, staffing, and processes, that may contribute to the errors occurring within a health care organization (Reason, 2000). Organizational factors for the current study included work shift and number of daily ER admissions. Additionally, the Swiss cheese model served as a foundation for this study by enabling me to focus on possible latent conditions, such as work shift and number of daily ER admissions, that may have contributed to the creation of duplicate records (i.e., active failures) created during the fast-track admissions process. The study findings would indicate the relationship between work shift, admissions, and the creation of duplicate records; therefore, health care administrators may reevaluate policies and procedures within the ER based on the findings.

## Literature Related to Key Variables or Concepts

This section provides a review of literature related to the key variables of the study. These variables included the number of duplicate record data entry errors, work shift, and number of daily ER admissions. I discuss previous studies about duplicate record data entry errors in addition to existing knowledge about ER overcrowding, fast-track admissions, the importance of data integrity in health care, and the maintenance and prevention of duplicate record data entry errors.

### Duplicate Record Data Entry Errors

Researchers have studied duplicate record data entry errors from various perspectives. McCoy et al. (2013) asserted that matching data entry fields such as first and last name and DOB could show whether record pairs were duplicates. Matching first and last name fields occurred in 16.6%–40.66% of records. McCoy et al. explained that the same set of records lacked a DOB, which decreased the range of matching records to 0.16%–15.47%. McCoy et al. also used confirmed duplicates to determine the most common duplicate record data entry errors and the potential causes of those errors. McCoy et al. pulled data from a variety of health care organizations in 10 different states. Just et al. (2016) and Qian et al. (2020) contended that the use of the middle name, SSN transpositions, and first and last name misspellings represented the highest contributors to duplicate records. Just et al. and Qian et al. added that blank fields existed within the patient record where patient information should have been captured, thereby causing the creation of duplicate records. Waldenburger et al. (2016) also identified duplicate records in the EHR of a large teaching hospital using probabilistic or deterministic record linkage, and they identified 1,708 true duplicate matches using deterministic record linkage and 273 true duplicate matches using probabilistic record linkage. Based on the results from these studies, duplicate medical records present an issue in health organizations. Previous research had not addressed the topic of duplicate record data entry errors created during fast-track admissions.

**Duplicate Record Error Rate**

Health care organization leaders use an error rate to determine the extent of the errors occurring. Researchers determine the error rate by dividing the total number of errors by the total number of patient encounters (Qian et al., 2020). For the current study, I determined the duplicate record rate by dividing the total number of duplicate record data entry errors confirmed on the duplicate report by the total number of admissions that occurred during the four staggered work shifts in the Alabama health system from March 2019 to September 2020. Duplicate record rates typically range between 5% and 10% for freestanding health care facilities such as hospitals or clinics. Additionally, health systems composed of multiple facility locations can have a duplicate error rate of up to 20% (Harris & Houser, 2018).

**ER Overcrowding**

ERs faced exponential growth that impacted quality of care and increased the risk for errors (Vanbrabant et al., 2019). ERs across the country faced challenges with overcrowding caused by high patient volumes and acuity combined with inadequate clinical support and bed capacity (King et al., 2020). Exceeding the bed capacity in the ER resulted in overcrowding which placed pressure on the staff and can result in human error (Hsieh et al., 2018; Weigl et al., 2016).

Patient encounters in the ER increased by 15% between 2009 and 2019, which represented an increase from 120 million to 138 million visits (Quattrini & Swan, 2019). The American College of Emergency Physicians defined overcrowding as an unequal ratio of patients needing emergency care and the ER's access to the resources needed to provide the care (Chrusciel et al., 2019). Additionally, overcrowding resulted in increased length of stay and decreased quality of care, which caused some ERs to divert their ambulances to surrounding ERs with availability to care for additional patients (Chrusciel et al., 2019; Flynn et al., 2017; Shen & Wang, 2015; Vanbrabant et al., 2019).

Spencer et al. (2019) explained that the Centers for Medicare and Medicaid Services developed national overcrowding measures under the Hospital Inpatient Quality Reporting Program initiative, which included median times from arrival to departure for discharged and admitted patients, patients leaving before being seen, and door-to-diagnostic evaluation by the health care provider. According to the authors, these measures required health care administrators to develop quality improvement processes to mitigate the overcrowding issue within the organization to improve patient flow, length of stay, and overall quality of care in the ER.

**Fast-Track Admissions Process**

ER managers implemented fast-track admissions in ERs to mitigate overcrowding and by moving patients through an expedited registration, so they are seen and discharged more efficiently (Freeman et al., 2017; Rogers et al., 2017). In this process, patients bypass the patient registration desk to go directly to triage. Once triaged, patients proceed to an exam room where a physician sees them and personnel completes the registration (Alishahi Tabriz et al., 2020 ; Gasperini et al., 2020). Leaders implemented fast-track admissions in about 80% of ERs in the United States (Hwang et al., 2015).

Administrators implemented several variations of fast-track admissions in ERs. First, organizations allow emergency care workers such as paramedics and nurses to assist patient registrars with data entry for registration to expedite the patient encounter (Flynn et al., 2017; Freeman et al., 2017). Structured frameworks showed that utilizing clinical workers increased the accuracy of collected data and the speed of transferring data to the ER staff (Flynn et al., 2017). Historically, paramedics served as external health care providers who respond to emergency calls for sick and injured patients and provide the appropriate care until more comprehensive care can be obtained in the ER (Hunter et al., 2020). Instead of allowing emergency care workers to assist with registration, organizations can keep the registration process exclusive to patient registrars. Personnel conduct fast-track separately, which enables them to register and triage patients in different areas of the ER (Hwang et al., 2015). Additionally, some organizations designate patient registrars and a clinical team to exclusively fast-track patients (Hwang et al., 2015).

The second variation of fast-track admissions involves the type of patients who can utilize the process. Typically, ER personnel use fast-track admissions for patients who present to the ER with non-urgent, specific, or minor trauma complaints that require a specialist (Gasperini et al., 2020). The emergency severity index serves as a common triage tool used by triage staff to determine if patient symptoms meet the fast-track criteria based on acuity and resources (Quattrini & Swan, 2019). The emergency severity index is a 5-level severity tool, which requires a severity ranking of 4 or 5 for the patient to progress through fast-track admissions (Quattrini & Swan, 2019). Additionally, the Institute for Healthcare Improvement (2020) provided more detailed inclusion criteria for triage staff because acuity and resources alone do not properly profile a fast-track patient (Quattrini & Swan, 2019). Once the patient meets the criteria for fast-tracking, they move to a room where they will see a physician, and personnel complete registration at the bedside (Alishahi Tabriz et al., 2020; Gasperini et al., 2020).

In this study, the two Alabama hospitals included many different aspects of the fast-track processes presented in the literature. First, the organizations fast-tracked all patients through the ER and did not limit this process to non-urgent, specific, or minor trauma complaints. Second, the Alabama health system also allowed whoever was sitting at the front entrance to take the patient’s name, DOB, and chief complaint. This person could be a security guard or police officer. The person who collected the information then passed it to the nurse conducting triage and finally to the patient registrar, who completed the registration in the exam room while the patient waited to see the physician. The health system developed the fast-track process to allow all ER patients, regardless of symptoms, to be seen and discharged more efficiently (Freeman et al., 2017; Rogers et al., 2017).

## Work Shift and Number of Daily Admissions

Work shift and the number of daily admissions represent organizational factors in an ER that may contribute to data entry errors. Health care administrators typically develop and modify policies and procedures to meet organizational needs; however, they may not recognize some organizational factors as potential causes for error because they may assume individuals always cause errors (Reason, 2000). To the best of my knowledge, there is no literature focused on whether number of daily ER admissions or work shift at the time of admission contributed to data entry errors. However, I did find literature connecting work shift and number of daily admissions to hospital medical errors.

### *Work Shift*

Previous research connected work shift to medical and data entry errors. Work shift and workload for health clinicians emerged as the most frequent causes of medical error and as contributing factors of incorrect patient order entry, with more errors identified during the night shift between the hours of 7 p.m. and 7 a.m. (Canfield et al., 2020; Cappadona et al., 2020). Leviatan et al. (2020) also showed work shift and workload caused physicians to commit prescription errors. A decision support system flagged a total of 3,738 prescription errors out of 1,682,896 orders requiring prescriptions. Levitian et al. claimed physicians were 8.2 times more likely to create prescription errors during a shift with an increased workload. Additionally, physicians working a double shift in contrast to a single shift also committed more prescription errors. Brigitta and Dhamanti (2020) showed work shift and workload caused nurses to commit medication administration errors. Brigitta and Dhamanti (2020) demonstrated medication administration errors were more prevalent when workload increased on a shift or when nurses worked night shifts or holidays. Night shifts and holidays emerged as significant variables for medication administration errors because nurses could experience fatigue and decreased sleep.

### *Number of Daily Admissions*

The literature suggested improvements in the ER admission process decreased overcrowding. ER overcrowding leads to inefficient admission to the ER and the hospital, especially to the intensive care unit (Lee et al., 2020). Lee et al. (2020) explained that an academic trauma center experienced severe overcrowding in the ER because of low availability of beds and a higher number of patients waiting to be admitted from the ER to the intensive care unit. The influx of patients typically occurred during midday hours at the hospital. ER dispositions prepared 2.5 hours in advance had a positive effect on admission to the intensive care unit by allowing more efficient coordination with the health care team, which decreased the length of stay in the ER.

## Importance of Data Integrity in Health Care

As information sharing becomes more prominent among health care organizations, data integrity plays an ever-more essential role in the provision of high-quality care and the resulting patient satisfaction (Gyamfi et al., 2017). *Data integrity* refers to the completeness and accuracy of patient data (Ayaad et al., 2019). Information sharing consists of data captured at multiple points of care (e.g., during the admissions process, primary or specialty physician encounters, lab or diagnostic imaging) and then accessed through a single EHR within a health system (Brundin-Mather et al., 2018). Previously, data integrity was only pertinent to research because researchers required accurate and consistent data for valid results, but health care systems now need to ensure data integrity before EHR implementation (Brundin-Mather et al., 2018). Duplicate record data entry errors may cause a barrier to EHR implementation. Additionally, systematic errors can occur during an EHR implementation, increasing the number of current data errors or causing a loss of data due to other organizational system conflicts, such as simultaneous system upgrades (Ward et al., 2013). Data integrity within health care applications ensures greater patient outcomes with improved documentation accuracy, thus, increasing quality of care and mitigating the risk of medical error (Gyamfi et al., 2017).

Health care facilities can implement several strategies to ensure the integrity of information stored in their health care applications. According to Lusk (2015), an information governance team at a pediatric health system developed measures to maintain data integrity at the facility, which included a standard naming convention policy stating the legal name could only be captured at registration. The author added that technical constraints were discussed in relation to the policy to ensure the system would recognize the data elements. Leaders developed a training program for patient registrars and other employees responsible for patient admissions and required everyone to pass the exam before gaining access to the health care applications used during the admissions process. Furthermore, Lusk explained that leaders created a feedback system to catch data entry errors created by individuals. Managers notified the individual of the error, provided constructive feedback, and the individual corrected the error.

## Maintenance and Prevention of Duplicate Record Data Entry Errors

Just et al. (2016) explained HIM professionals and hospital administrators invested in technology and education to maintain the integrity of the data in their health care applications and to prevent the occurrence of data entry errors. Just et al. added simple number transpositions, name misspellings, or duplicate records have resulted in negative implications. Several strategies appeared in the literature for maintaining and preventing data entry errors.

### *Duplicate Record Cleanups*

Martin (2016) described duplicate record cleanup as a manual process that involves merging duplicate records after confirming they match using a review of demographic data such as first and last name, address, DOB, and SSN. Martin asserted the process also involved moving documents from one paper record to the next if the health care facility's records were hybrid or electronic in each health care application, such as the EHR, lab, or imaging systems. As such, Martin explained that administrators completed record merges in a master application such as the MPI or EHR before correcting the record in other applications.

The HIM department or an external consulting organization often completes duplicate record cleanups. Professional duplicate cleanups cost up to $96 per chart (Banton & Filer, 2014; Nelson, 2015). Crew et al. (2021) explained a duplicate record cleanup at a health system performed by the HIM department and involved the identification, verification, and merging of duplicate records. Medical records in ancillary systems (i.e., lab and radiology) were merged with the new medical record in the health system's enterprise MPI (Crew et al., 2021). Dooling et al. (2016) explained HIM professionals who were American Health Information Management members participated in a survey regarding their participation in duplicate record cleanups within their organizations. Survey results indicated over half of the 815 HIM professionals that participated in the survey conducted their own cleanup processes on a routine basis.

### *Ongoing Training and Education*

Patient registrars and other health care workers who capture admission data into the MPI need training and education. Patient registrars conduct patient registration in addition to completing insurance verification, assisting patients and families with navigational and wheelchair assistance, and maintaining patient flow in the ER to improve the overall patient experience (Barton & Shelton, 2018). However, other personnel also conduct admissions tasks as doctors, nurses, and paramedics help patients get seen sooner, depending on the structure of the fast-track process in the facility (Barton & Shelton, 2018; Leventhal & Schreyer, 2020; Martin, 2016; Prints et al., 2020; Sauer, n.d.). Leaders must provide ongoing training opportunities, such as delivering learning modules that focus on accurate data capture and patient verification. Feedback sessions following discovered errors also may minimize future errors (Martin, 2016).

## Summary

Duplicate record data entry errors present a problem in the ER. After ER visits increased by 15% between 2009 and 2019, rising from 120 million to 138 million visits

(Flynn et al., 2017; Quattrini & Swan, 2019), health care leaders implemented fast-track ER admissions to mitigate overcrowding and expedite the admission process for patients with low-acuity symptoms (Flynn et al., 2017). Fast-track admissions allow patients to bypass the registration desk and go directly to triage (Gasperini et al., 2020). After triage, the patient moves to an exam room where they will see the physician, and personnel complete patient registration at the bedside (Alishahi Tabriz et al., 2020; Gasperini et al., 2020; Hwang et al., 2015). Duplicate record data entry errors occur often in the United States; however, many health care professionals do not recognize the impact of these errors until they negatively affect patient care (Banton & Filer, 2014; Lippi et al., 2017). Previous studies on duplicate record data entry errors showed first and last name misspellings and DOB and SSN transpositions as the most common in the patient record (Just et al., 2016; McCoy et al., 2013). Little was known about the number of duplicate record data entry errors created during fast-track admissions in the ER or if variables such as work shift and number of daily admissions contribute to duplicate record data entry errors. Some researchers discussed how the time of day might impact medical errors, ER overcrowding, and admissions from the ER to hospital units. I designed the current study to provide information on how work shift and number of daily admissions may contribute to the number of duplicate record data entry errors created during fast-track ER admissions at two acute care hospitals in an Alabama health care system.

Chapter 3 provides a discussion of the methods used to conduct the study. Chapter sections include the following: research design and rationale; population, sampling, and sampling procedures; archival data; data analysis; ethical procedures; and threats to validity.

# Chapter 3: Research Method

Duplicate record data entry errors complicate fast-track ER admissions. The number of patients admitted to the ER increased over the past 10 years (Quattrini & Swan, 2019). In response, health care leaders implemented fast-track ER admissions to mitigate overcrowding and expedite the admission process for patients with low-acuity symptoms (Flynn et al., 2017; Quattrini & Swan, 2019). ER administration and HIM professionals must understand the possible impacts that work shift and number of daily admissions may have on the number of duplicate record data entry errors occurring during fast-track ER admissions. The purpose of this correlational quantitative study was to examine the associations between work shift, number of daily ER admissions, and number of duplicate record data entry errors (i.e., misspelling of first and last name or address, incorrect DOB, and transposed SSN) at two acute care hospitals in an Alabama health care system.

Inferential statistics involve examining potential relationships among groups (McGregor, 2018). The inferential statistical tests used for the current study included chi-square test of independence, Kruskal-Wallis H test, and simple and multiple linear regression. The Kruskal-Wallis H test is appropriate for studies focused on determining significant differences in the independent variable between multiple groups (Belhekar, 2016). The chi-square test of independence determines whether two variables are independent (Wagner & Gillespie, 2019). Simple linear regression involves the evaluation of a single dependent and independent variable (Osborne, 2017). Multiple linear regression is appropriate for studies in which researchers predict variable values based on the value of other multiple variables (Knapp, 2018). This chapter provides a discussion of the study's research methods, including the research design and rationale and the methodology consisting of population, sampling, sampling procedures, archival data, data analysis threats to validity, and ethical procedures.

## Research Design and Rationale

Work shift and number of daily admissions served as the study's independent variables, and the number of duplicate record data entry errors served as the dependent variable. Errors included the misspelling of first and last names and transposed SSNs at two acute care hospitals in an Alabama health care system. I chose a quantitative correlational research design. In quantitative correlational studies, researchers examine and measure relationships or effects of variables using numerical systems to reveal the relationships between the variables (Edmonds & Kennedy, 2017). I measured these relationships using appropriate statistical testing. Quantitative research is also deductive and can be generalized to a larger population (Edmonds & Kennedy, 2017; Morgan, 2014). The results from this study may be generalizable to other ERs that rely on fast-track admissions and experience duplicate record data entry errors. Quantitative research designs provide the framework for data analysis because statistical tests are determined by the type of independent and dependent variable (Osborne, 2017). A quantitative design was appropriate for the current study because the independent variables (work shift and number of daily admissions) and dependent variable (number of duplicate data entry errors) were continuous and categorical.

Additionally, quantitative correlational designs can be experimental or nonexperimental. The current study was nonexperimental because I did not manipulate the independent variables (see Wilson & Joy, 2017). In quantitative studies, researchers must also determine the amount of time it will take to collect data so they can allow an appropriate amount of time to collect all data and organize it in IBM's SPSS software (Wagner & Gillespie, 2019).

## Methodology

### Population

The target population for this study involved two hospitals in an Alabama health system with 125 and 323 beds. Both hospitals relied on fast-track ER admissions and followed similar processes. Both facilities admitted all patients seen in the ERs, regardless of the complaint, through fast-track. The ER admissions for both hospitals combined were approximately 548. I collected data over 19 months between March 2019 and September 2020.

### Sampling and Sampling Procedures

The sample size included all confirmed duplicate ER admissions at the two Alabama hospitals, so I collected data on all ER admissions between March 2019 and September 2020. I included confirmed duplicates in the data set after the hospital staff reviewed the duplicate report and confirmed that the data sets within the report were true duplicates created by data entry errors (e.g., misspelling of first and last names and transposed SSNs). I downloaded G*Power Version 3.1.9.4 from g-power.apponic.com and used it to compute a sample size for each RQ.

RQ1: What is the association between the work shift and the number of duplicate record data entry errors for fast-track ER admissions?

For RQ1, I used the chi-square test of independence and the Kruskal-Wallis H test. The chi-square test of independence determines whether two variables are independent of one another (Wagner & Gillespie, 2019). This test focused on determining whether duplicate record data entry errors were independent of each of the four staggered shifts. Additionally, duplicate record data entry errors were recoded to “no errors recorded” and “errors recorded.” No errors recorded represented each shift with no errors, and errors recorded represented the shifts with errors. The Kruskal-Wallis H test is a rank-based nonparametric test that can be used to determine whether there are statistically significant differences between two or more groups of an independent variable (Belhekar, 2016). This test focused on determining whether differences existed in the number of duplicate record data entry errors by work shift. The analysis of covariance (ANCOVA) could not be conducted because of assumption violations and the number of ER admissions not being available per shift. The chi-square test of independence and the Kruskal-Wallis H test were appropriate for determining associations between the number of duplicate record data entry errors and the work shift.

I measured the dependent variable on a continuous scale, and the independent variable included two or more categorical groups (see Knapp, 2018). Work shift was a nominal categorical variable because it involved four staggered work shifts determined by the time the patient was admitted to the ER. I included the following parameters: alpha = 0.05, power = 0.80, and effect size = 0.25 (see Appendix A). In addition to a standard confidence interval of 0.95, I used an error probability of 0.05 because this was standard for rejecting the hypothesis. I used the medium effect size (i.e., 0.15 and 0.25) for RQs 1–3 because this is the recommended effect size in social sciences (see Brydges, 2019). Additionally, a higher power with a smaller effect size would have required a larger sample size, which may not have been realistic for the study, producing results not beneficial to the public (see Kraemer & Blasey, 2016). A lower power with a smaller sample size would have increased the probability of rejecting the null hypothesis because the sample would not have been large enough to yield accurate results, requiring a higher effect size (see Kraemer & Blasey, 2016). A moderate effect size, however, allowed me to use a realistic sample size. The calculated minimum sample size was 179 confirmed duplicate record pairs.

RQ2: What is the association between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions?

For RQ2, I used the test statistic simple linear regression; however, I used multiple linear regression in G*Power: fixed model, $R2$ deviation from zero. I used simple linear regression to evaluate associations between a single independent and dependent variable (see Osborne, 2017). The parameters included the following: alpha = 0.05, power 0.80, and effect size = 0.15. The calculated minimum sample size was 55 confirmed duplicates (see Appendix A).

RQ3: What is the association between the work shift, number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions?

For RQ3, I used multiple linear regression: fixed model, *R*2 deviation from zero. Multiple linear regression was appropriate for this study because it can be used to predict variable values based on the value of other multiple variables (see Knapp, 2018). For the current study, the number of duplicate record data entry errors depended on the number of daily ER admissions. I measured the dependent variable on a continuous scale, and the independent variable included two or more categorical or continuous groups (see Knapp, 2018). The number of duplicate record data entry errors and the number of daily ER admissions were continuous variables. The parameters included the following: alpha = 0.05, power = 0.80, and effect size = 0.15. The calculated minimum sample size was 68 confirmed duplicate record data entry errors (see Appendix A). The duplicate report typically includes 20–30 confirmed duplicates per month, and I included 19 months of data in the report for this study, which totaled 356 samples. This supported the minimum sample sizes for all tests.

**Archival Data**

I analyzed a custom-built duplicate medical record report consisting of duplicate record data entry errors from fast-track admissions. The duplicate report the HIM department pulls from Paragon did not have the elements needed for the study; therefore, the HIM director worked with IT to build a custom duplicate record report. The duplicate report alerts the HIM director of potential duplicate records, and once generated from Paragon, HIM staff confirm whether each record set is a true duplicate by completing a manual verification process that compares name, address, insurance, signature, and SSN verification across various software applications. The HIM director helped me obtain the duplicate report, and staff members identified the data entry errors that caused the initial duplicate records for each duplicate pair. Errors included misspellings of first and last names and transposed SSNs from March 2019 to September 2020. The HIM director de-identified the report of all PHI and identified all record pairs using Record 1, Record 2 before releasing the report to me. I counted all data entry errors from the confirmed duplicates to determine the total number of errors made between March 2019 and September 2020 during different work shift hours (i.e., four staggered shifts in the 24 hours between 5:00 a.m. and 5:00 a.m.). The HIM director provided the number of total admissions in a separate report. I determined the number of daily ER admissions in SPSS using the admissions and duplicate record report. I was unable to determine the number of admissions per shift because there were only daily admission totals included on the report. I determined work shift using the time of admission to the ER for each patient record.

I received a signed business associate agreement and a data agreement from the health system in Alabama granting permission for me to receive duplicate patient records from both rural hospitals. Both agreements were also used to obtain final institutional review board (IRB) approval (IRB Number 11-09-21-0693638). I organized data in IBM's SPSS Version 27 and conducted a Kruskal-Wallis H test, chi-square test of independence, and simple and multiple linear regression.

**Instrumentation and Construct Operationalization**

The independent and dependent variables for this study appear in Table 1. I used two independent variables and one dependent variable.

**Table 1**

*Summary of Research Variables*

| Variable name | Variable type | Coding |
|---|---|---|
| Work shift | Categorical/independent | Work shift 1 = 5:00 a.m. to 11:00 a.m.<br>Work shift 2 = 11:00 a.m. to 5:00 p.m.<br>Work shift 3 = 5:00 a.m. to 11:00 p.m.<br>Work shift 4 = 11:00 p.m. to 5:00 a.m. |
| Duplicate record data entry errors | Continuous/dependent | Numerical value for the total number of duplicate records between March 2019 and September 2020 during work shift hours<br>First and last name misspellings<br>SSN transpositions |
| Number of daily ER admissions | Continuous/independent | Numerical value for the total number of daily admissions between March 2019 and September 2020 during work shift hours |

*Note*. DOB = date of birth; SSN = social security number, ER = emergency room. The duplicate record data entry errors (dependent variable) were recoded to “no errors recorded” and “errors recorded.” No errors recorded represented each shift with no errors, and errors recorded represented the shifts with errors.

***Number of Daily ER Admissions***

Daily ER admissions served as the first independent variable, and it was a continuous variable. The number of daily ER admissions represented the number of patient admissions into the ER. I obtained this number from the  admission and duplicate record reports provided by the HIM director occurring between March 2019 and September 2020.

### *Work Shift*

Work shift served as the second independent variable, and it was a categorical variable. Work shift referred to the shift worked by the ER patient registrar. I determined work shift by referring to the patient admission time listed on the duplicate report. I coded the work shifts as follows: Shift 1 = 5:00 a.m. to 11:00 a.m., Shift 2 = 11:00 a.m. to 5:00 p.m., Shift 3 = 5:00 p.m. to 11:00 p.m., Shift 4 = 11:00 p.m. to 5:00 a.m.

### *Duplicate Record Data Entry Errors*

The duplicate record data entry errors served as the dependent variable. These errors consisted of misspellings of first and last names and transposed SSNs. I confirmed with the HIM department that DOB and address errors did not appear in the duplicate report. Error totals were differentiated by type and hospital in addition to the total number of errors for both hospitals. The duplicate record data entry errors were also a continuous variable, and I measured them using the manual identification completed by the HIM staff. I documented the error identification of the duplicate report for each duplicate record pair occurring between March 2019 and September 2020 during the hours of each work shift.

## Data Analysis Plan

I conducted data analysis using IBM's SPSS Version 27. SPSS provides a platform for statistical analysis used often in quantitative studies (Knapp, 2018). The duplicate report included the following data elements: duplicate pairs designated by

Record 1, Record 2 in place of PHI, arrival date and time to the ER, and data entry errors that caused the initial duplicate record for each confirmed duplicate pair. I defined errors as misspelling of first and last names and transposed SSNs. The HIM director and staff removed all PHI before releasing the report to me. I worked closely with the HIM director to ensure the report included only relevant data elements. I also completed additional screening after receiving the report to determine whether it contained data that should be removed. Researchers should conduct data screening to identify unnecessary and inconsistent data in a collected data set (Toepoel, 2016). There were several duplicated rows of data on the report. I confirmed with the HIM staff that the data was duplicated data and not duplicate records.

There were several missing months of data (January, February, and October 2019). I noted this information and asked the HIM director if data were available for each month. I received the data for October 2019, but the director confirmed that not all data elements were present for January and February 2019, which resulted in data being removed from the data set for these months (HIM director, personal communication, December 6, 2021).

The following RQs and hypotheses guided the study:

RQ1: What is the association between the work shift and the number of duplicate record data entry errors for fast-track ER admissions?

$H_0 1$: There is no association between the work shift and the number of duplicate record data entry errors for fast-track ER admissions.

$H_a1$: There is an association between the work shift and the number of duplicate record data entry errors for fast-track ER admissions.

RQ2: What is the association between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions?

$H_02$: There is no association between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions.

$H_a2$: There is an association between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions.

RQ3: What is the association between the work shift, number of daily ER admissions, and the number of duplicate record data entry errors for fast-track ER admissions?

$H_03$: There is no association between the work shift, number of daily ER admissions, and the number of duplicate record data entry errors for fast-track ER admissions.

$H_a3$: There is an association between the work shift, number of daily ER admissions, and the number of duplicate record data entry errors for fast-track ER admissions.

Researchers use the chi-square test of independence to determine whether two variables are statistically independent (Wagner & Gillespie, 2019). The Kruskal-Wallis H test is a rank-based nonparametric test that researchers use to determine whether statistically significant differences exist between two or more groups of an independent variable (Belhekar, 2016). RQ1 guided an exploration of whether duplicate record data entry errors were independent of each shift and if differences existed in the number of duplicate record data entry errors by work shift. I measured the dependent variable on a continuous scale, and the independent variable included four groups. The number of duplicate record data entry errors (dependent variable) represented continuous variables in this study. Work shift (independent, grouping variable) served as a nominal categorical variable because it was characterized by one of four staggered shifts worked at the time the patient was admitted to the ER.

I made additional assumptions for the chi-square test of independence and the Kruskal-Wallis H test to ensure the validity of the results and the appropriateness of the statistical test. Both tests needed to meet independence of observations, which means the residuals associated with the observation of the dependent variable are not associated with other observations (See Farmer & Farmer, 2021; See Wagner & Gillespie, 2019). I tested these assumptions using IBM's SPSS. For the chi-square test of independence, I also assumed that cells needed expected counts of at least 5 (See Wagner & Gillespie, 2019). I tested this assumption by verifying cells in a contingency table had a frequency of five or greater (See Farmer & Farmer, 2021). Additional assumptions for the Kruskal-Wallis H test included whether the distribution of the scores of each group (i.e., shift) had the same shape. I used box plots to test this assumption (See Belhekar, 2016).

Simple linear regression works for studies with a single independent variable and dependent variable (Osborne, 2017). Knapp (2018) deemed multiple linear regression appropriate for studies in which researchers predict the values of variables based on the value of other multiple variables. I measured the dependent variable on a continuous scale, and the independent variable included two or more categorical or continuous groups. The number of duplicate record data entry errors and the number of daily ER admissions were continuous, and work shift served as a categorical nominal variable.

Additional assumptions for single and multiple linear regression first included the required presence of a linear relationship between the dependent and independent variables (Knapp, 2018). I used scatterplots and partial regression plots to test for this assumption. Knapp also advised homoscedasticity must also be present, and studentized residuals against unstandardized predicted values need to be plotted. Data must also not present multicollinearity, which involves a high correlation of independent variables. I inspected correlation coefficients and tolerance values. No significant outliers can be present in the data, so I used casewise diagnostics and studentized deleted residuals to test for outliers (see Knapp, 2018). Lastly, residuals should be normally distributed, so testing involved the use of a histogram or plot of studentized residuals (see Knapp, 2018). I used IBM's SPSS to conduct testing for assumptions. Assumptions were violated for ANCOVA in RQ 1, and I could not continue with the test because of the violations and limited data for the number of daily ER admissions.

I interpreted results for the chi-square of independence, Kruskal-Wallis H test, and simple and multiple linear regression tests based on the alpha level of 0.05 and the *p*-value. I performed pairwise comparisons for the Kruskal-Wallis H test using IBM's SPSS and Dunn's 1964 procedure with a Bonferroni correction for multiple comparisons (see Knapp, 2018). I considered a result less than or equal to the *p*-value to be a statistically significant result. I accepted or rejected null and alternate hypotheses accordingly.

## Threats to Validity

*External validity* refers to the ability to generalize the study findings to the greater population (Edmonds & Kennedy, 2017). One threat to generalizability in the current study involved the hospitals using fast-track admission processes. Other hospitals may use both fast-track and traditional admission processes, therefore, limiting the generalization of these findings. *Internal validity* refers to how successfully an implemented research design determines relationships among variables (Edmonds & Kennedy, 2017). A threat to internal validity in this study involved the duplicate report. The HIM employee in the data integrity department identified the duplicate record data entry errors on the duplicate report because the errors were manually identified. This employee could have made errors, inadvertently skewing the types of errors identified during analysis.

## Ethical Procedures

I submitted the IRB application to Walden University for approval to work with patient records on the duplicate report. The health system in Alabama signed a business associate agreement granting permission for the author to receive the data set for duplicate patient records from both rural hospitals. I also required the HIM director, who was the primary contact at the facility, to sign a data use agreement outlining specifics for the study and for the data that would be collected. I had an ethical concern related to the duplicate report's inclusion of PHI consisting of first and last name, DOB, and SSN. To protect patient privacy, the HIM director removed all PHI from the report after completing the manual verification of true duplicates. Each duplicate pair was identified as Record 1, Record 2. Data from the duplicate report was confidential. Members of my dissertation committee and I were the only individuals with access to the data. The HIM director emailed the data to me, and I securely stored it on my personal laptop. When not in use, I locked the laptop so it could not be accessed without a thumbprint. I deleted the data from my laptop in its entirety when it was no longer needed.

## Summary

I used a quantitative correlational design for the current study. Researchers adopt quantitative correlational designs to examine relationships among groups in ways that can be generalized to a larger population (Edmonds & Kennedy, 2017; Morgan, 2014). Collected data represented ER admission numbers at two Alabama hospitals for the months between March 2019 and September 2020. I examined duplicate records from ER fast-track admissions during the time frame using a duplicate report produced by the health care system. The duplicate report alerts the HIM staff at the facility of potential duplicate records. The HIM staff manually verified true duplicates and then removed PHI from the report. I counted errors identified from the confirmed duplicates. The HIM director provided a report with a combined total of hospital admissions for the Alabama Health system. I determined the number of daily ER admissions in IBM's SPSS using the admissions and duplicate record report. I identified work shift using the time of ER admission for each patient record.

I performed data analysis using IBM's SPSS. The analysis consisted of Kruskal-Wallis, chi-square test of independence, simple and multiple linear regression statistical tests to determine associations between the dependent variable (the number of duplicate record data entry errors) and the independent variables (work shift and number of daily ER admissions). I followed processes for interpreting results and assessing assumptions for each statistical test. Chapter 4 provides a discussion of the results of the data collection and analysis.

# Chapter 4: Results

The purpose of this correlational quantitative study was to examine the associations between work shift, number of daily ER admissions, and number of duplicate record data entry errors (i.e., misspelling of first and last name or address, incorrect DOB, and transposed SSN) at two acute care hospitals in an Alabama health care system. At the time of this study, no other research existed on the creation of duplicate record data entry errors and fast-track admissions. Fast-track ER admissions in this study referred to all ER visits that occurred during the study time frame of March 2019 to September 2020. The following RQs and hypotheses guided this study:

RQ1: What is the association between the work shift and the number of duplicate record data entry errors for fast-track ER admissions while controlling for the number of daily ER admissions?

$H_0$1: There is no association between the work shift and the number of duplicate record data entry errors for fast-track ER admissions while controlling for the number of daily ER admissions.

$H_a$1: There is an association between the work shift and the number of duplicate record data entry errors for fast-track ER admissions while controlling for the number of daily ER admissions.

RQ2: What is the association between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions?

$H_0$2: There is no association between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions.

$H_a2$: There is an association between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions.

RQ3: What is the association between the work shift, number of daily ER admissions, and the number of duplicate record data entry errors for fast-track ER admissions?

$H_03$: There is no association between the work shift, the number of daily ER admissions, and the number of duplicate record data entry errors for fast-track ER admissions.

$H_a3$: There is an association between the work shift, the number of daily ER admissions, and the number of duplicate record data entry errors for fast-track ER admissions.

Chapter 4 provides an explanation of the data collection techniques and a description of the results from the statistical tests for each RQ.

## Data Collection

This section addresses data collection techniques for the study. I received IRB approval to conduct the study from Walden University on November 9, 2021. I requested secondary data on the duplicate report from the HIM director of the Alabama Health System on November 9, 2021, and received a response on November 29, 2021.

### Data Collection Time Frame and Participants

The secondary data came from the duplicate report that the HIM department reviewed for potential duplicate medical records during the time frame of March 2019 to September 2020. The report consisted of patient records that had been verified as true duplicates. Data entry errors only involved mistakes in name and SSN at both facilities. The HIM staff confirmed potential duplicates by comparing name, address, DOB, and SSN; however, no DOB or address errors appeared in the data set. According to Just et al. (2016), first and last name, DOB, and SSN are common demographic fields used to confirm duplicate medical records; however, DOB errors decreased from 14.9% to 6.2% in 2016. Internal messaging within the health system, which can include the submission of a medical record number correction form, verbal communication, or email, alerts the HIM staff of potential duplicate medical records. This process allows the HIM staff to proactively correct data entry errors before review of the duplicate report (HIM director, personal communication, February 17, 2023).

Patient arrival time was also included and recoded according to the four different work shifts occurring between 5:00 a.m. and 5:00 a.m. I combined duplicates on the duplicate report for both hospitals in the Alabama health system. To ensure compliance with the Health Insurance Portability and Accountability Act, the HIM director de-identified PHI (i.e., name, DOB, address, SSN) for all of the patient records listed on the report and identified each duplicate pair as Record 1 and Record 2. Table 2 displays the errors differentiated by type and facility. Between both facilities, name errors represented the highest error types, and Hospital 2 had the highest number of errors.

**Table 2**

*Error Types by Facility*

| Error type | Hospital 1 | | Hospital 2 | | Total | |
|---|---|---|---|---|---|---|
| | *N* | % | *N* | % | *N* | % |
| Name | 69 | 92.0% | 268 | 95.4% | 337 | 94.7% |
| Social security number | 6 | 8.0% | 13 | 4.6% | 19 | 5.3% |
| Date of birth | 0 | 0% | 0 | 0% | 0 | 0% |
| Address | 0 | 0% | 0 | 0% | 0 | 0% |
| Total | 75 | 100.0% | 281 | 100.0% | 356 | 100.0% |

**Data Collection Limitations**

The original data collection time period had to be modified because of limitations with available data. After reviewing the initial data set, I discovered that data were missing for the months of January, February, and October of 2019. The HIM director sent the missing data for October 2019 (personal communication, December 6, 2021); however, various fields, such as admission date, time, and data entry error type were not available for January and February 2019. Therefore, I excluded these months of data from the data set and established March 2019 to September 2020 as the new study time frame.

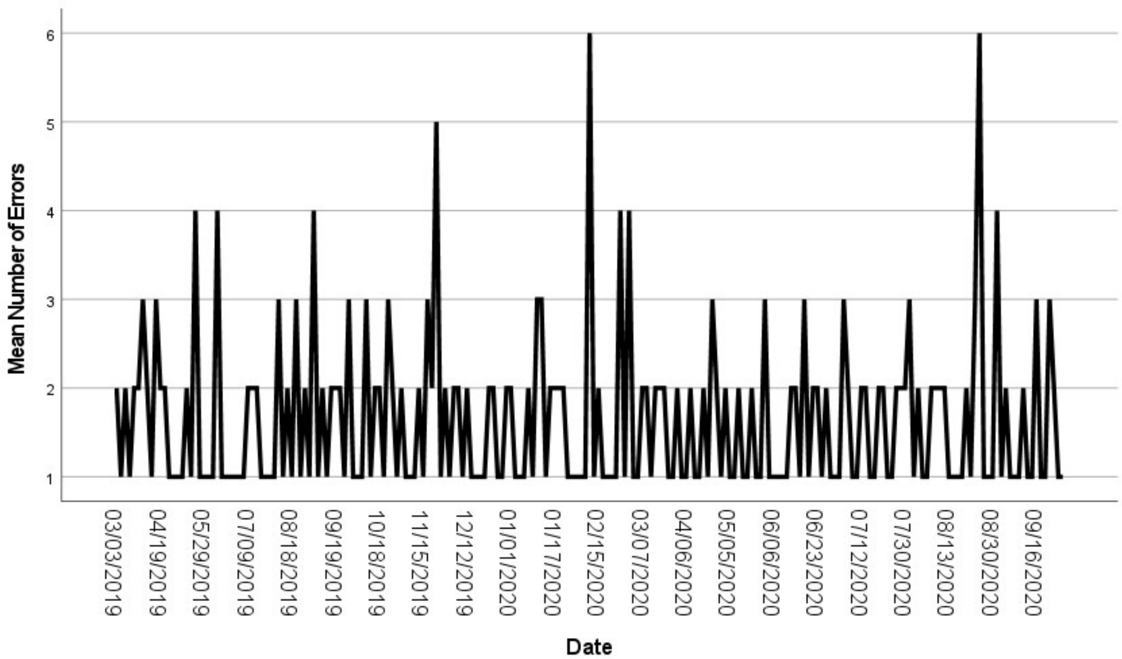
Another limitation of available data involved the daily admissions report. I received a separate report with the total hospital admissions during the time frame of March 2019 to September 2020. However, the daily admissions report included the aggregate total of 23,455 admissions for both hospitals in the Alabama Health System without breaking down the admissions for the ER. I determined the number of daily ER admissions (14,528 including no error days and 8,927 including days with errors) in SPSS using the admissions and duplicate record report, but I could not distinguish the number of daily ER fast-track admissions by shift admissions, which limited the ANCOVA analysis for RQ1.

**Data Cleaning**

Data cleaning was performed on the original duplicate report. The report included multiple hospital departments with duplicate records. The HIM director explained that the report was a comprehensive review of potential duplicate records in all departments for both facilities (personal communication, December 3, 2021); therefore, the report had to be filtered for the duplicate records at two Alabama hospitals' ERs. Once the duplicate report was filtered and the daily admissions were added, the data represented 548 total days during the study time frame, which included 217 days with errors and 331 days with no errors. Figure 2 shows the number of duplicate record data entry errors during the study time frame and ranged between two and six errors per day. I excluded multiple rows of duplicated data. The HIM staff confirmed these data as duplicate rows of data, which included the same patient demographics but no admission information. The data showed 356 errors that spanned 217 days.

**Figure 2**

*Line Frequency of Errors*




## Results

### ANCOVA/Kruskal-Wallis/Chi-Square: RQ1

RQ1: What is the association between the work shift and the number of duplicate record data entry errors for fast-track ER admissions while controlling for the number of daily ER admissions?

$H_0$1: There is no association between the work shift and the number of duplicate record data entry errors for fast-track ER admissions while controlling for the number of daily ER admissions.

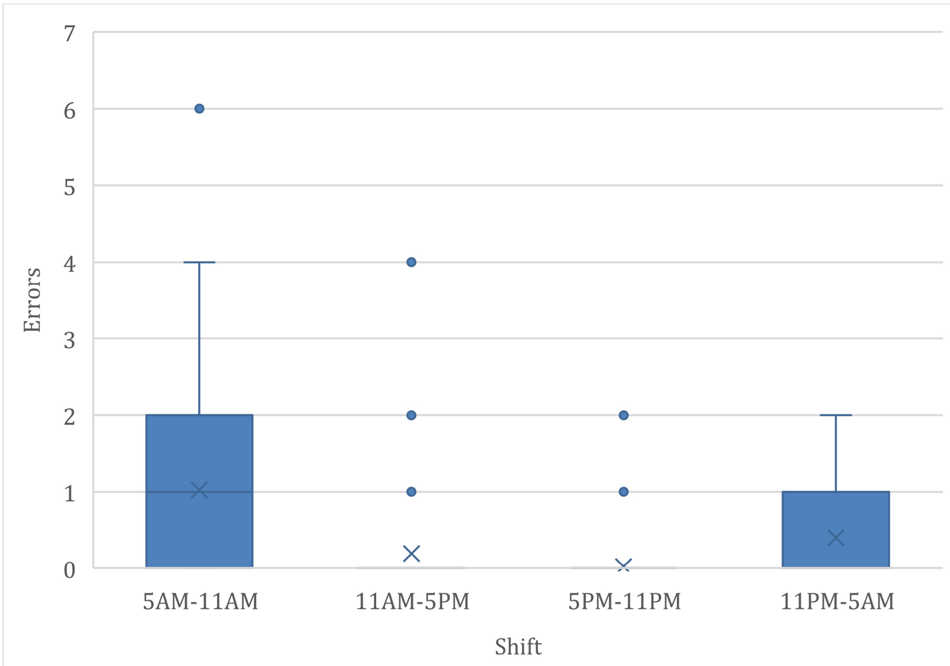
*$H_a$1*: There is an association between the work shift and the number of duplicate record data entry errors for fast-track ER admissions while controlling for the number of daily ER admissions.

Five assumptions must be satisfied to run an ANCOVA. These assumptions include having (a) a dependent and covariate variable that is measured on a continuous scale, (b) an independent variable that includes two or more categorical groups, (c) a covariate that is linearly related to the dependent variable at each level of the independent variable, (d) homogeneity of regression slopes, and (e) homogeneity of variances (Knapp, 2018). The study's overall design met the first two assumptions for RQ1. The dependent variable (number of duplicate record data entry errors) and the covariate (number of daily ER admissions) were continuous. The independent variable of work shift was a categorical variable and was characterized by shift worked out of four staggered shifts and the time the patient was admitted to the ER. The third assumption (the covariate is linearly related to the dependent variable at each level of the independent variable) was not met as assessed using a scatterplot of the number of duplicate record data entry errors against the number of admissions for each shift (see Knapp, 2018; see Appendix B). The fourth assumption (homogeneity of regression slopes) was not met as assessed by the statistically significant interaction between the covariate and the independent variable (Knapp, 2018; see Appendix B). The fifth assumption (homogeneity of variances) was not assessed because the third and fourth assumptions were violated, establishing that an ANCOVA was not appropriate (see Knapp, 2018).

I used a chi-square test of independence and a Kruskal-Wallis H test to analyze the data instead of an ANCOVA because the ER admissions had been reported per day instead of per shift and because of the violations to the assumptions necessary to perform the ANCOVA. The chi-square test of independence determines whether two variables are statistically independent (Wagner & Gillespie, 2019). The chi-square test of independence has three assumptions that must be met: the presence of (a) two nominal variables, (b) independence of observations, and (c) all cells having expected counts of at least 5 (Wagner & Gillespie, 2019). The first two assumptions were met by the study design. The third assumption was met with no expected cell counts of fewer than 5 (see Wagner & Gillespie, 2019). The Kruskal-Wallis H test is a rank-based nonparametric test researchers can use to determine whether statistically significant differences exist between two or more groups of an independent variable (Belhekar, 2016). The Kruskal-Wallis H test had four assumptions that needed to be met: (a) one continuous dependent variable, (b) one independent variable that consists of two or more categorical independent groups, (c) independence of observations, and (d) the distribution of the scores of each shift have the same shape (Belhekar, 2016). The study design met the first three assumptions. Assessment by visual inspection of a box plot revealed that the fourth assumption was met. The box plot revealed that the errors recorded were not similar for all shifts, and errors were the highest on Shifts 1 and 4 (see Belhekar, 2016; see Figure 3).

**Figure 3**

*Box Plot for Distribution of Errors*




I used a chi-square test of independence to determine whether duplicate record data entry errors were independent of the shift. During the study period, there were 217 days of errors across the four shifts. For this analysis, there were 217 shifts with an opportunity for errors and no errors to occur. I recoded the number of errors as "no errors recorded" and "errors recorded." No errors recorded represented each shift with no errors, and errors recorded represented the shifts with errors. If no association emerged between the shift and whether errors were recorded, I expected a similar distribution of errors and no errors across the four shifts. There was a strong, statistically significant association between the number of duplicate record data entry errors recorded and the work shift: $\chi2(3) = 254.697$, $p < 0.001$, Cramer's V = 0.542. The test indicated 148 out of 217 shifts

(68.2%) with errors between 5:00 a.m. and 11:00 a.m.; 35 out of 217 shifts (16.1%) with errors between 11:00 a.m. to 5:00 p.m.; four out of 217 shifts (1.8%) with errors between 5:00 p.m. and 11:00 p.m., and 71 out of 217 shifts (32.7%) with errors between 11:00 p.m. and 5:00 a.m. Therefore, duplicate record data entry errors occurred differently across the four working shifts (see Table 3).

**Table 3**

*Chi-Square Results: Recorded Duplicate Records Data Entry Errors and Shift*

| Errors recorded | 5:00 a.m. to 11:00 a.m. | | 11:00 a.m. to 5:00 p.m. | | 5:00 p.m. to 11:00 p.m. | | 11:00 p.m. to 5:00 a.m. | |
|---|---|---|---|---|---|---|---|---|
| | *N* | % | *N* | % | *N* | % | *N* | % |
| No | 69 | 31.8 | 182 | 83.9 | 213 | 98.2 | 146 | 67.3 |
| Yes | 148 | 68.2 | 35 | 16.1 | 4 | 1.8 | 71 | 32.7 |
| Total | 217 | 100.0 | 217 | 100.0 | 217 | 100.0 | 217 | 100.0 |

*Note.* $\chi 2 = 254.697$; $df = 3$; $p$ value $< 0.001$; Cramer's V = 0.542.

I conducted a Kruskal-Wallis test to determine whether there were differences in the number of errors recorded between shifts: Shift 1 = 5:00 a.m. to 11:00 a.m., Shift 2 = 11:00 a.m. to 5:00 p.m., Shift 3 = 5:00 p.m. to 11:00 p.m., Shift 4 = 11:00 p.m. to 5:00 a.m. Table 4 shows that the number of errors recorded was statistically significantly different between the shifts, $\chi 2(3) = 262.856$, $p < 0.001$.

**Table 4**

*Independent-Samples Kruskal Wallis Test Summary*

| | |
|---|---|
| *N* | 868 |
| Test statistic | 262.856 |
| *df* | 3 |
| *p* value | < 0.001 |

Subsequently, I performed pairwise comparisons using Dunn's 1964 procedure with a Bonferroni correction for multiple comparisons (see Table 5). The post hoc analysis revealed statistically significant differences in the number of recorded errors between the 5:00 a.m. to 11:00 a.m. shift (mean rank = 608.75), the 11:00 p.m. to 5:00 a.m. shift (mean rank = 443.70), the 11:00 a.m. to 5:00 p.m. shift (mean rank = 372.21), and the 5:00 p.m. to 11:00 p.m. shift (mean rank = 313.34), with all having $p < 0.05$ (see Table 4). Shift 1 had significantly more errors than shifts 2, 3, and 4.

**Table 5**

*Pairwise Comparisons of Shift Results*

| Pairwise comparisons of shift | | Standard error | Standard test statistic | *p* value | Adjusted *p* value |
|---|---|---|---|---|---|
| Sample 1/Sample 2 | Test statistic | | | | |
| 5:00 p.m. to 11:00 p.m./ 11 a.m. to 5 p.m. | 58.873 | 19.310 | 3.049 | 0.002 | 0.014 |
| 5:00 p.m. to 11:00 p.m./11:00 p.m. to 5:00 a.m. | (-)130.357 | 19.310 | (-)6.751 | 0.000 | 0.000 |
| 5:00 p.m. to 11:00 p.m./5:00 a.m. to 11:00 a.m. | 295.406 | 19.310 | 15.298 | 0.000 | 0.000 |
| 11:00 a.m. to 5:00 p.m. /11:00 p.m. to 5:00 a.m. | (-)71.484 | 19.310 | (-)3.702 | 0.000 | 0.001 |
| 11:00 a.m. to 5:00 p.m. /5:00 a.m. to 11:00 a.m. | 236.532 | 19.310 | 12.249 | 0.000 | 0.000 |
| 11:00 p.m. to 5:00 a.m. /5:00 a.m. to 11:00 a.m. | 165.048 | 19.310 | 8.547 | 0.000 | 0.000 |

## Simple Linear Regression: RQ2

RQ2: What is the association between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions?

$H_0$2: There is not an association between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions?

$H_a$2: There is an association between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions?

I used a simple linear regression to analyze the second research question. I examined associations between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions. Six assumptions must be satisfied to run a simple linear regression. These assumptions include: (a) a dependent variable that is continuous, (b) an independent variable that consists of two or more categorical or continuous groups, (c) the presence of a linear relationship between the dependent and independent variables, (d) the presence of homoscedasticity, (e) no significant outliers, and (f) normal distribution of residuals (Knapp, 2018). The overall research design met the first two assumptions for this research question. The dependent variable (number of duplicate record data entry errors) was continuous, and the independent variables (work shift and the number of daily admissions) included two or more categorical and continuous groups. The third assumption (i.e., the presence of a linear relationship) was confirmed by a scatterplot displaying a small spread of residuals (See Appendix C). Additionally, there was an approximate independence of residuals, evaluated by a Durbin-Watson statistic of 2.332 (see Appendix C). The fourth assumption (i.e., the presence of homoscedasticity) was confirmed by visual inspection of a plot of standardized predicted values shown in Figure 3 (see Knapp, 2018). I determined homoscedasticity was present because the spread of the residuals did not increase or decrease across the predicted values.

I confirmed the fifth assumption (i.e., no significant outliers) by identifying cases with standardized residuals greater than 3 (see Knapp, 2018; see Appendix C). I identified three outliers (i.e., days with five and six recorded errors that were retained in the dataset). After removing them, the regression model then identified all days with four recorded errors as outliers. Thus, the removal did not improve the model fit. I confirmed the sixth assumption (i.e., normal distribution of residuals) by determining the values of the mean and standard deviation on the histogram of the standardized residuals, which were 0 and 1. Additionally, the residuals were normally distributed on the P-P plot (see Knapp, 2018; see Appendix C).

I conducted a simple linear regression to understand the associations between the number of daily fast-track emergency admissions and the number of duplicate record data entry errors for fast-track ER admissions. I plotted a scatterplot of duplicate errors against the number of daily admissions which indicated a linear relationship between the variables. Table 6 shows the prediction equation: number of errors = 1.062 + 0.014 * daily admissions. The number of fast-track admissions statistically predicted the number of duplicate record data entry errors, *AF*(1, 215) = 7.140, $p = 0.008$. There was a predicted increase in errors of 0.014 *(95%* CI:0.004 - 0.024) for every additional person admitted. The $R^2$ value revealed a 3.2% variance in the number of errors as explained by the number of admissions. The association between the number of duplicate record data entry errors and the number of daily fast-track ER admissions was not significant, but the results revealed the admissions can predict the number of errors. Figure 4 reveals several days with higher admissions and errors although the errors are not significant.

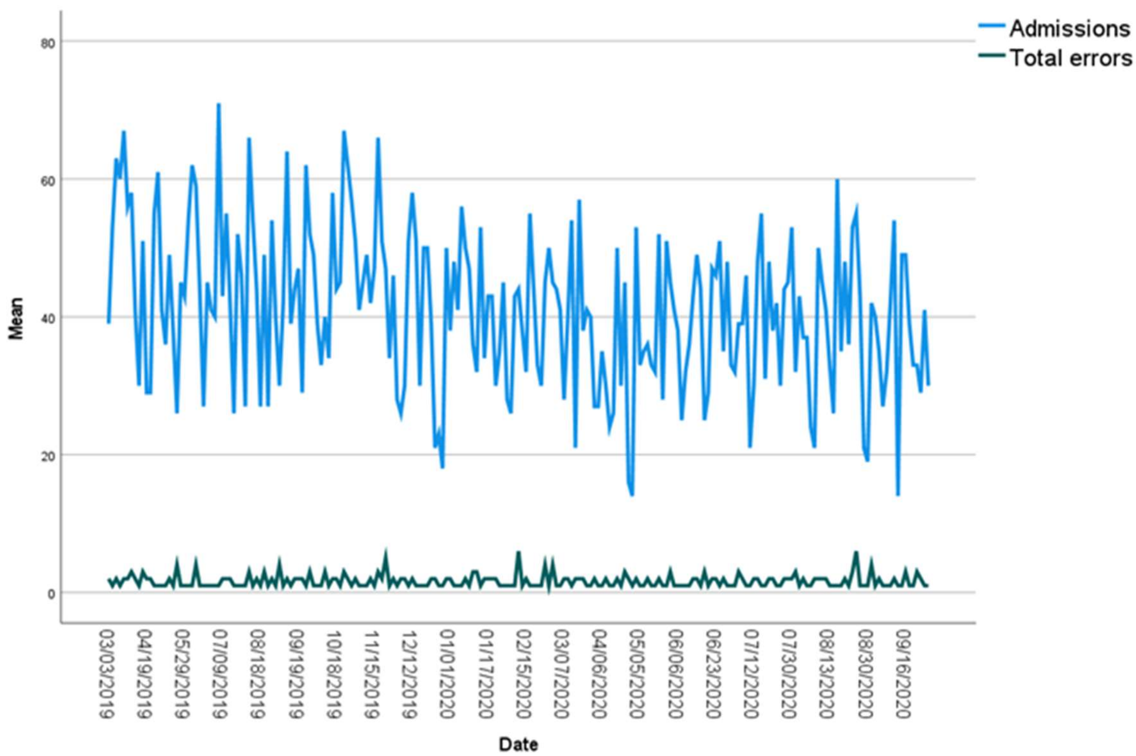
**Table 6**

*Coefficients for Admissions*

| Model | | Unstandardized coefficients | | Standardized coefficients | $t$ | $p$ value | 95% CI for B | |
|---|---|---|---|---|---|---|---|---|
| | | B | Standard error | Beta | | | Lower bound | Upper bound |
| 1 | (Constant) | 1.062 | 0.225 | | 4.730 | 0.000 | 0.620 | 1.505 |
| | Admissions | 0.014 | 0.005 | 0.179 | 2.672 | 0.008 | 0.004 | 0.024 |

**Figure 4**

*Line Frequency of Admissions and Errors*




**Multiple Linear Regression: RQ3**

RQ3: What is the association between the work shift, number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions?

$H_0 3$: There is no association between the work shift, number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions.

$H_a 3$: There is an association between the work shift, number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions.

I used multiple linear regression to analyze the third research question, examining associations between the work shift, number of daily ER admissions, and the number of duplicate record data entry errors for fast-track ER admissions. The assumptions, which were the same as those for simple linear regression in RQ2, were met.

I conducted a series of simple linear regression tests for each shift to determine any associations between the work shifts, number of daily ER admissions, and the number of duplicate record data entry errors for fast-track ER admissions. I could not determine daily ER admissions per shift because the admissions report only provided aggregate totals. I plotted scatterplots of duplicate record data entry errors per work shift to understand the effect of daily ER admissions on duplicate record data entry errors. Figure 5 indicated a linear relationship between the variables for shift 1 because the residuals were normally distributed on the P-P plot. Additionally, the linear regression results also revealed $F(1, 215) = 13.022$, indicating a significant association between duplicate record data errors and the number of daily ER admissions based on $p < 0.0001$ (see Table 7). Figures 6–8 indicated no linear relationship between the number of daily ER admissions and the number of duplicate record data entry errors for Shifts 2, 3, and 4.

**Figure 5**

*Simple Linear Regression Scatterplot: Shift 1 (5:00 am to 11:00 a.m.)*

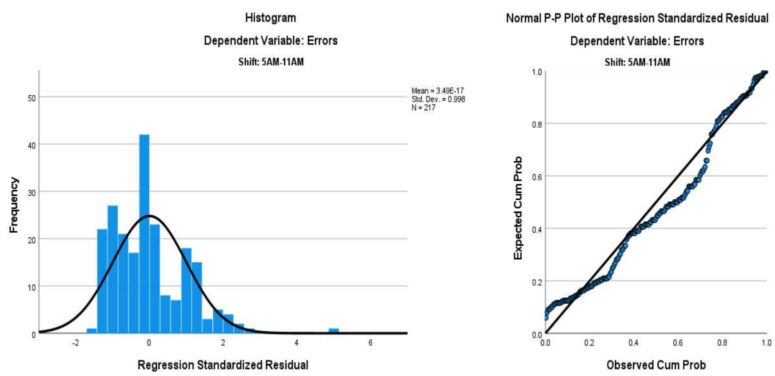



**Figure 6**

*Simple Linear Regression Scatterplot: Shift 2 (11:00 a.m. to 5:00 p.m.)*

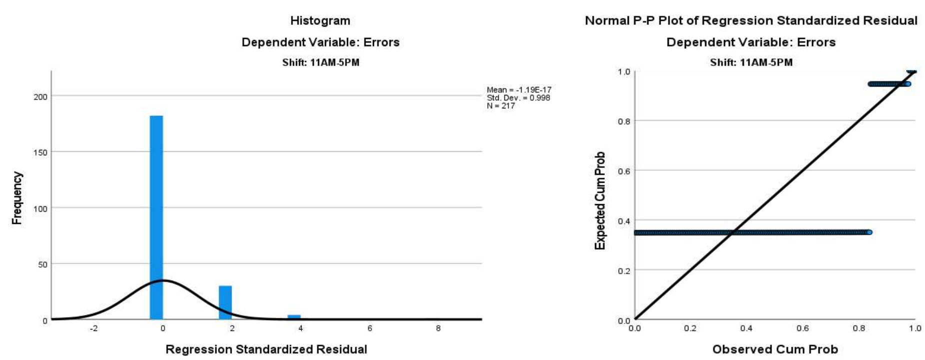


**Figure 7**

*Simple Linear Regression Scatterplot: Shift 3 (5:00 p.m. to 11:00 p.m.)*

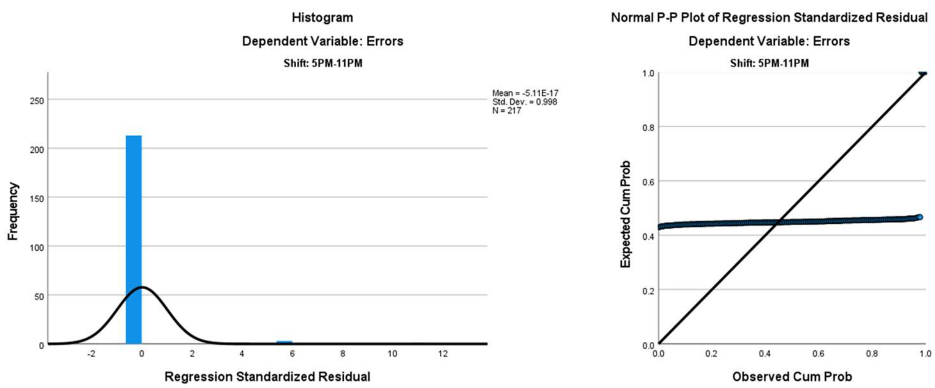
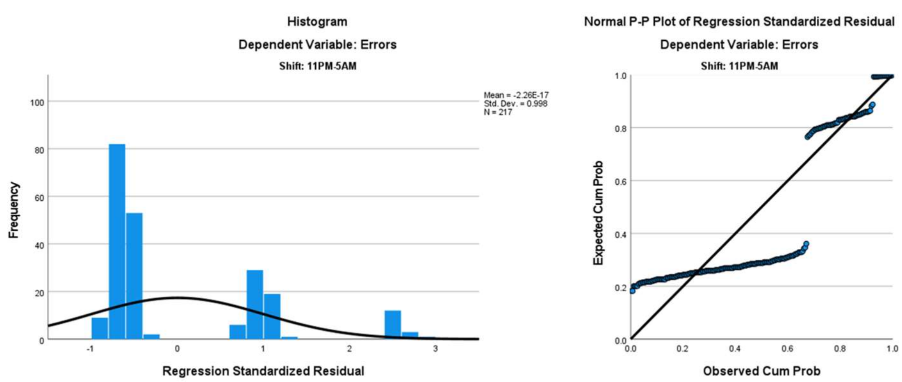



**Figure 8**

*Simple Linear Regression Scatterplot: Shift 4 (11:00 p.m. to 5:00 a.m.)*




The number of daily admissions was not a significant predictor of the number of duplicate record data entry errors during Shifts 2, 3, and 4. The number of daily admissions accounted for 5.7% of the variation in the number of errors during Shift 1 indicating a strong, significant association between the number of daily admissions and duplicate record data errors. I assumed that the strong significance of errors for Shift 1 was due to the higher number of admissions during that time; however, there is no admissions data per shift to confirm this assumption.

**Table 4**

*Multiple Linear Regression: Coefficients*

| Shift | Unstd. coefficients | | Std. coefficients | *t* | *p* value | Result | $R^2$ |
|---|---|---|---|---|---|---|---|
| | B | Std. error | Beta | | | | |
| 5:00 a.m. to 11:00 a.m. | | | | | | | |
| (Constant) | 0.211 | 0.233 | | 0.906 | 0.366 | | |
| Admissions | 0.020 | 0.005 | 0.239 | 3.609 | < 0.001* | $F(1, 215) = 13.022$, $p < 0.001$ | 0.06 |
| 11:00 a.m. to 5:00 p.m. | | | | | | | |
| (Constant) | 0.192 | 0.127 | | 1.510 | 0.133 | | |
| Admissions | 4.218E05 | 0.003 | 0.001 | 0.014 | 0.989 | $F(1, 215) = 0.0002$, $p = 0.989$ | 9.345E-07 |
| 5:00 p.m. to 11:00 p.m. | | | | | | | |
| (Constant) | 0.011 | 0.045 | | 0.241 | 0.809 | | |
| Admissions | 0.000 | 0.001 | 0.019 | 0.276 | 0.783 | $F(1, 215) = 0.076$, $p = 0.783$ | 3.543E-04 |
| 11:00 p.m. to 5:00 a.m. | | | | | | | |
| (Constant) | 0.648 | 0.158 | | 4.108 | 0.648 | | |
| Admissions | -0.006 | 0.004 | -0.110 | -1.626 | -0.006 | $F(1, 215) = 2.643$, $p = 0.105$ | 0.01 |

## Summary

This chapter provided the statistical results for the RQs in the current study. I conducted a chi-square test of independence for the first RQ to determine statistically significant associations between the work shift and duplicate record data entry errors for fast-track ER admissions. There was a strong, statistically significant association between the work shift and the number of duplicate record data entry errors, $\chi2(3) = 254.697$, $p <$

0.001, Cramer's V = 0.542. I also conducted a Kruskal-Wallis H test to determine if there were differences in the number of duplicate record data entry errors between the four staggered shifts, and the test indicated a statistically significant relationship. Additionally, I performed pairwise comparisons using Dunn's 1964 procedure with a Bonferroni correction for multiple comparisons. Statistically significant differences emerged in recorded errors between the 5:00 a.m. to 11:00 a.m. shift (mean rank = 608.75), the 11:00 p.m. to 5:00 a.m. shift (mean rank = 443.70), the 11:00 a.m. to 5:00 p.m. shift (mean rank = 372.21), and the 5:00 p.m. to 11:00 p.m. shift (mean rank = 313.34), all with $p < 0.05$.

I conducted a simple linear regression on the second RQ to determine a statistically significant association between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions. The $R^2$ value (.179) showed the number of admissions accounted for 3.2% of the variation in the number of duplicate record data entry errors indicating an association between the number of daily fast-track ER admissions. Although the association is not significant, the number of daily fast-track ER admissions can predict the number of duplicate record data entry errors.

I ran multiple linear regression tests on the third RQ to determine any associations between the work shifts, number of daily ER admissions, and the number of duplicate record data entry errors for fast-track admissions. The number of daily admissions was not useful in statistically significantly predicting the number of errors during Shifts 2, 3, and 4; however, it was useful in statistically significantly predicting the number of errors during Shift 1, $F(1, 215) = 13.022$, $p < 0.001$. The number of daily admissions accounted for 5.7% of the variation in the number of errors during shift 1 indicating a strong, significant association between the number of daily ER admissions and duplicate record data entry errors. Chapter 5 presents an interpretation of the findings, the study limitations, recommendations, and implications.

# Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this correlational quantitative study was to examine the associations between work shift, number of daily ER admissions, and number of duplicate record data entry errors (i.e., misspelling of first and last name or address, incorrect DOB, and transposed SSN) at two acute care hospitals in an Alabama health care system. Research had shown that duplicate record data entry errors present a problem in the patient registration department of the ER, but I found no previous research on duplicate record data entry errors created during fast-track ER admission processes. Results of the current study may help hospital leaders understand whether variables such as work shift and number of daily ER admissions predict duplicate record data entry errors. I analyzed secondary data provided by the HIM director of an Alabama health system to answer each of the three RQs.

For RQ1, I conducted a Kruskal-Wallis H test and a chi-square test of independence to determine statistically significant associations between work shift and number of duplicate record data entry errors for fast-track ER admissions. I found a strong, statistically significant association between the number of duplicate record data entry errors and the work shift. Of 217 shifts, 148 of 217 shifts (68.2%) with errors occurred from 5:00 a.m. to 11:00 a.m., 35 out of 217 shifts (16.1%) with errors occurred from 11:00 a.m. to 5:00 p.m., four out of 217 shifts (1.8%) with errors occurred from 5:00 p.m. to 11:00 p.m., and 71 out of 217 shifts (32.7 %) with errors occurred from 11:00 p.m. to 5:00 a.m.

For RQ2, I conducted a simple linear regression to determine statistically significant differences between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions. The number of fast-track admissions statistically predicted the number of duplicate record data entry errors; however, only 3.2% of errors were accounted for, which indicated an association between the number of daily fast-track emergency admissions and the number of duplicate record data entry errors. There was a slight increase in errors for every additional admission.

For RQ3, I conducted multiple linear regression tests for each shift to determine any associations between work shifts, number of daily ER admissions, and number of duplicate record data entry errors for fast-track ER admissions. I could not determine daily ER admissions for each shift because I received aggregate totals on the admissions report; however, the linear regression tests revealed a linear relationship between the variables for Shift 1 (5:00 a.m. to 11:00 a.m.). A linear relationship between the variables was not present for Shift 2 (11:00 a.m. to 5:00 p.m.), Shift 3 (5:00 p.m. to 11:00 p.m.), or Shift 4 (11:00 p.m. to 5:00 a.m.).

## Interpretation of the Findings

### RQ1

The first RQ addressed associations between the work shift and the number of duplicate record data entry errors for fast-track ER admissions. There was an association between the number of duplicate record data entry errors and the shift; specifically, the analysis showed most occurrences of errors (68.2%) were on Shift 1 (5:00 a.m. to 11:00

a.m.). The results are inconsistent when compared to Cappadona et al. (2020) and Canfield et al. (2020) who found that more medical errors occur during the night shift between 7:00 p.m. and 7:00 a.m. In contrast, Manias et al. (2019) reported that medical errors typically occur between 7:00 a.m. and 3:00 p.m. My study revealed that only 1.8% of errors were reported on Shift 3 (5:00 p.m. to 11:00 p.m.) and 32.7 % on Shift 4 (11:00 p.m. to 5:00 a.m.). There were also large percentages of no errors recorded on Shift 2 (98.2%), Shift 3 (83.9%), and Shift 4 (67.3%). Aljabari and Kadhim (2021) stated that underreporting can occur because of the work environment, which may include a high workload or a lack of system functionality or established procedure for notifying staff of potential medical errors. The ER typically offers the first line of care for patients, and it may periodically experience an influx of admissions resulting in a higher workload (Lozano-Lozano et al., 2021). Although more errors appeared on Shift 1 (5:00 a.m. to 11:00 a.m.) in the current study, I could not determine whether there was a higher workload during that time because the number of daily ER admissions was not reported by shift.

**RQ2**

The second RQ addressed associations between the number of daily ER admissions and the number of duplicate record data entry errors for fast-track ER admissions. There was a significant association between the number of daily ER admissions and the number of duplicate record data entry errors. Although this was a small percentage, the number of daily ER admissions impacted the number of duplicate record data entry errors created during fast-track ER admissions. Increased admissions can cause health care workers to rush through tasks, causing medical errors that occur in up to 1 in 20 admissions (Brennan et al., 2020; Trovó et al., 2020). It is possible that emergency care workers are not properly verifying the accuracy of patient information upon arrival to the ER to quickly get the patient registered and seen by the physician. Data for the time of day of each admission were not included in this study because the report only listed the number of admissions per day and not their times. Therefore, I could not determine whether there was an influx of patient admissions at certain times of day. Lee et al. (2020) reported that increased patient admissions occur during midday hours in the ER. My study results are the first to demonstrate that daily ER fast-track admissions predict duplicate record data entry errors.

**RQ3**

The third RQ addressed associations between work shift, number of daily ER admissions, and number of duplicate record data entry errors for fast-track ER admissions. There was a statistically significant association between the number of duplicate record data entry errors and the number of daily ER admissions, specifically for Shift 1 (5:00 a.m. to 11:00 a.m.). The number of daily ER admissions accounted for 5.7% of the variation in the number of duplicate record data entry errors during Shift 1, indicating a strong, significant association between the number of daily ER admissions and the number of duplicate data entry errors. The number of daily ER admissions was a predictor for the number of duplicate record data entry errors for Shift 1. Data were unavailable to determine admissions per shift; however, it is possible that Shift 1 may have had an increased number of ER admissions, which may have caused the increased number of errors. Leviatan et al. (2020) reported a higher likelihood of physicians creating more prescription errors during a shift with an increased workload.

**Error Rate**

The error rate, which is determined by dividing the total number of errors by the total number of admissions, represents the percentage of errors found in health care organizations (Qian et al., 2020). The total number of duplicate record data entry errors during the current study time frame of March 2019 to September 2020 was 356. The total number of hospital admissions was 23,455, and the number of ER admissions was 8,297. The health system duplicate record error rate was 1.5%, and the ER duplicate record error rate was 4%. Garza et al. (2022) explained the all-fields error rate includes the total population measured and represents an optimistic rate. The populated field error rate includes the error population and represents a conservative rate. Multiple error rates allow for reporting variability of errors within the organization (Garza et al., 2022). The all-fields or optimistic error rate for this study was low but indicative of potential processes to mitigate errors (see Garza et al, 2022). The daily monitoring of the duplicate report and communication among staff within the health system may be a contributor to the all-fields error rate (HIM director, personal communication, February 17, 2023). The populated field error rate was slightly higher and may indicate an issue with the creation of duplicate record data entry errors during fast-track ER admissions.

The current study error rates cannot be compared to the error rates reported by Harris and Houser (2018), which were up to 20% for large health systems, because it is unknown whether fast-track admission processes were used at other health care organizations and the impact this may have had on the creation of duplicate record data entry errors. My study is the first to present data on the impact that fast-track admissions may have on the creation of duplicate record data entry errors in the ER. Additionally, the Alabama Health System is smaller, with only two hospitals, in comparison to larger health systems with multiple hospitals and clinics, which may also have an impact on the number of reported errors.

**Interpretation of the Findings in Relation to the Theoretical Framework**

Human error theory served as the theoretical framework in this study. Reason (2000) developed the human error theory, which includes the person and system models. I used the system model as the foundation of this study because it focuses on organizational factors and system processes that may impact the creation of duplicate record data entry errors during fast-track ER admissions. In contrast, the person model directs blame for errors onto the responsible individual. Aljabari and Kadhim (2021) stated that individual blame allows health care leaders to avoid evaluating other organizational factors that may have contributed to the error. Watson (2016) found that inadequate procedures for capturing accurate data resulted in errors. In the current study, I focused on the organizational factors of work shift and number of daily ER admissions that may be associated with the creation of duplicate record data entry errors during ER fast-track admissions. This approach was consistent with the system model of the human error theory.

The Swiss cheese model further defines the system model of human error theory. Larouzee and Le Coze (2020) stated that system processes should prevent errors;

however, active failures or latent conditions allow holes to develop in those processes. Larouzee and Le Coze described active failures as acts that result in errors, and they asserted that latent conditions are caused by organizational factors. The results from the current study align with the errors found by Burns (2017) and Watson (2016) because the errors I found represented active and latent failures. Burns and Watson asserted that some errors resulted from individual acts and others were caused by organizational factors. The organizational factors from the current study (work shift and number of daily ER admissions) may be considered a latent condition for the Alabama Health System because the factors contribute to the number of duplicate record data entry errors created during ER fast-track admissions. Additionally, these conditions may represent dormant causes for duplicate record data entry errors that were not initially considered by organizational leaders at the Alabama Health System (see Larouzee & Le Coze, 2020).

## Limitations of the Study

The limitations discussed in Chapter 1 of this study were resolved; however, some were consistent throughout data collection and analysis. First, I assumed the data provided on the duplicate report would be accurate. This assumption was met because the employee confirmed the duplicate pairs on the report were true; however, data entry errors only included name and SSN because the HIM department worked with patient registrars and other hospital staff to proactively correct data entry errors (HIM director, personal communication, February 17, 2023). Findings for the current study were limited as I could only examine the two error types (name and SSN).

Second, the HIM staff employee expressed concern about completing the manual verification of the duplicates in a timely manner. This assumption was met because the employee completed the manual verification ahead of time. Third, I assumed the number of duplicate record data entry errors would fall between 420 and 630 to meet the minimum sample size requirements. There were only 356 confirmed duplicate record data entry errors due to the data discrepancies outlined in Chapter 4. However, I still conducted data analysis for each RQ and produced meaningful results.

Fourth, the data collected from the duplicate and admissions report continued to be limited for this study. Other organizational factors may be involved as possible contributors to the errors, but the duplicate report was limited to the specific types of data that were displayed. The health system provided the number of daily ER admissions on a separate report; however, I could not separate the data to display admissions per shift. Therefore, I modified the data analysis methods for RQ1, limiting the results for RQ3. The results still revealed associations and predictors for the creation of duplicate record data entry errors during ER fast-track admissions. Fifth, data continued to be limited only to ER admissions as the duplicate report listed admissions from other locations within the hospital. The generalizability of the study results may be limited to other hospitals and health systems with ER fast-track admissions that use a proactive approach to mitigating data entry errors.

## Recommendations

I have several recommendations for further research on this study's topic. The number of daily ER admissions per shift is needed to determine possible associations between work shift and number of duplicate record data entry errors. The study results revealed the number of daily ER admissions accounted for a variance in the number of duplicate record data entry errors; however, the number of daily admissions per shift could also determine the duplicate record error rate per shift. Although I determined the health system and ER error rates using the total number of admissions and duplicate record errors during the study time frame, the error rate per shift would provide additional insight into the impact that the number of daily ER admissions has on duplicate record data entry errors for each shift. Additionally, the time of day for each patient admission would be helpful in determining when the errors occurred. Several variations appeared in the literature regarding when errors were most likely to occur in hospitals and the ER (Canfield et al. 2020; Cappadona et al., 2020; Manias et al., 2019), but I could not determine the specific times for the current study even though the results revealed a variance in the number of daily admissions for Shift 1.

Additional research should also be conducted on this topic to include multiple hospitals or health systems or a larger health system, such as a teaching hospital in the sample population. Harris and Houser (2018) stated that larger health systems can present a duplicate record error rate of up to 20%. Additionally, previous studies on duplicate record data entry errors have included a teaching hospital and up to 71 multiple hospitals across several countries (Cohen et al., 2019; Waldenburger et al., 2016). To extend the knowledge from the current study, researchers could examine any associations in duplicate record data entry errors, work shift, and number of daily ER admissions between health systems that admit patients using a fast-track process based on nonurgent symptoms and those organizations such as the Alabama health system that fast-track all patients regardless of symptoms (see Gasperini et al., 2020). Finally, researchers could assess the reporting capabilities of the facilities to ensure the secondary data are robust and contain few limitations. This will ensure all variables can be analyzed for the most accurate results.

## Implications

### Implications for Social Change

The study results may promote social change because this is the first study to address the creation of duplicate record data entry errors during fast-track ER admissions with a focus on how the number of daily ER admissions and work shift contribute to error creation. Previous studies on duplicate record data entry errors were limited and emphasized only the types of errors and the potential causes of those errors. Work shift and number of daily admissions had not been considered as potential root causes (Qian et al., 2020). Current results may extend knowledge of duplicate record data entry errors to HIM professionals and ER leaders from a national and international level, highlighting the need to evaluate how work shift and number of daily admissions contribute to duplicate record data entry errors. The study results may also extend knowledge to ERs with fast-track admission processes. HIM professionals and ER leaders may implement new workflow or workflow policies and procedures to mitigate the risk of organizational factors such as work shift and number of daily admissions impacting the creation of duplicate record data entry errors during fast-track admission.

**Implications for Practice**

The study results revealed statistically significant associations between the number of duplicate record data entry errors and work shift, with more duplicate record data entry errors recorded on Shift 1 than any other shift in the Alabama health system ERs. Associations appeared between the number of duplicate record data entry errors and the number of daily ER admissions, indicating a 3.2% variance in the number of daily ER admissions accounted for the number of duplicate record data entry errors. Furthermore, 5.7% of daily ER admissions accounted for the number of duplicate record data entry errors on Shift 1. This information matters to HIM professionals and ER leaders because it indicates organizational factors (e.g., work shift and the number of daily ER admissions) contributed to the creation of duplicate record data entry errors during fast-track admissions on Shift 1.

It may be beneficial for Alabama health system ER leaders to evaluate the workflow on Shift 1 to mitigate the creation of duplicate record data entry errors. The fast-track admission process at the Alabama health system consisted of a paramedic, a security guard, or a police officer obtaining the patient's name, DOB, and chief complaint. After this information was collected, the triage nurse entered the data into the system, and the patient registrar completed the registration once the patient entered the exam room. Therefore, ER leaders may consider providing enhanced training with an emphasis on patient verification to ensure each employee verifies the patient's information is correct (Cohen, 2019; Harris & Houser, 2018). Patient verification should represent an important step for the Alabama health system because multiple workers capture patient demographics that are entered into the system. Researchers have shown inadequate patient verification can cause duplicate record data entry errors (Leventhal & Schreyer, 2020; Prints et al., 2020). It may be possible that personnel fail to perform this step at each phase of the fast-track admission process if there is an increased number of admissions, as on Shift 1. HIM professionals could also use the results from this study to collaborate with ER leaders to ensure the proper steps, such as modified workflows, policies, and procedures, are taken to mitigate duplicate record data entry errors during fast-track ER admissions.

## Conclusion

Duplicate record data entry errors represent a common challenge in health care organizations across the country. Previous literature centered around duplicate record data entry errors exists; however, the problem remains unresolved. This study contributes new knowledge about contributors to the creation of duplicate record data entry errors during ER fast-track admissions. The study showed statistically significant associations among work shift, the number of daily admissions, and the number of duplicate record data entry errors created during ER fast-track admissions. Additionally, this study is the first to shed light on these organizational factors. ER leaders and HIM professionals can use this knowledge to modify workflow, policies, and procedures that may mitigate the creation of duplicate record data entry errors during fast-track admissions. Duplicate record data entry errors impact the data integrity of the medical record, which not only impacts the HIM industry but the overall health care system. Data integrity, which the medical record reflects, serves as an essential factor in quality care (Gyamfi et al., 2017).

Health care leaders must maintain medical record accuracy to ensure quality care and patient satisfaction.

References

Alishahi Tabriz, A., Trogdon, J. G., & Fried, B. J. (2020). Association between adopting emergency department crowding interventions and emergency departments' core performance measures. *American Journal of Emergency Medicine*. https://doi.org/10.1016/j.ajem.2019.04.048

Aljabari, S., & Kadhim, Z. (2021). Common barriers to reporting medical errors. *The Scientific World Journal*, *2021*, 1–8. https://doi.org/10.1155.2021.6494889

American Health Information Management Work Group. (2016). Best practices for patient matching at patient registration recommended best practices for accurate patient matching. *Journal of AHIMA*, *87*(10), 74–81.http://bok.ahima.org/doc?oid=301906#.WM0y0zsrLD4

Ayaad, O., Alloubani, A., Alhajaa, E. A., Farhan, M., Abuseif, S., Al Hroub, A., & Akhu-Zaheya, L. (2019). The role of electronic medical records in improving the quality of health care services: Comparative study. *International Journal of Medical Informatics*, *127*, 63–67. https://doi.org/10.1016/j.ijmedinf.2019.04.014

Banton, C. L., & Filer, D. L. (2014). The impact of multiple master patient index records on the business performance of health care organizations. *Journal of Technology Research*, *5*, 1–11.

Barton, J., & Shelton, D. (2018). *Transforming patient access and engagement*. Healthcare Financial Management Association. https://hfma.org/topics/article/62346.html

Belhekar, V. (2016). *Statistics for psychology using R*. SAGE Publications.

https://dx.doi.org/10.4135/9789353282493

Biddle, M. (2015). Maintaining the master patient index: The impact of patient registration processes on data integrity. *Applied Research Projects*, *32*. https://doi.org/10.21007/chp.hiim.0016

Brennan, P. A., Martino, M. M., Ponnusamy, S., White, R., De Martino, R., & Oeppen, R. S. (2020). Review: Avoid, trap, and mitigate- an overview of threat and error management. *British Journal of Oral and Maxillofacial Surgery*, *58*(2), 146–150. https://doi.org/10.1016/j.bjoms.2020.01.009

Brigitta, I. R., & Dhamanti, I. (2020). Literature review: Cause factor analysis and an effort to prevent medication administration error (MAE) at hospital. *Unnes Journal of Public Health*, *9*(2), 98–107. https://doi.org/10.15294/ujph.v9i2.36470

Brundin-Mather, R., Soo, A., Zuege, D. J., Niven, D. J., Fiest, K., Doig, C. J., & Stelfox, H. T. (2018). Secondary EMR data for quality improvement and research: A comparison of manual and electronic data collection from an integrated critical care electronic medical record system. *Journal of Critical Care*, *47*, 295–301. https://doi.org/10.1016/j.jcrc.2018.07.021

Brydges, C. (2019). Effect size guidelines, sample size calculations and statistical power in gerontology. *Innovation in Aging*, *3*(4). https://doi.org/10.1093/geroni/igz036

Burns, L. R. (2017). *Systemic and human factors that contribute to medical error: A study of higher reliability* [Doctoral dissertation, University of Houston]. ProQuest Dissertations and Theses Global.

Canfield, C., Udeh, C., Blonsky, H., Hamilton, A. C., & Fertel, B. S. (2020). Limiting the number of open charts does not impact wrong patient order entry in the emergency department. *JACEP Open*, *1*(5), 1071–1077. https://doi.org/10.1002/emp2.12129

Cappadona, R., Di Simone, E., De Giorgi, A., Boari, B., Muzio, M., Di Greco, P., Manfredini, R., Aurora Rodríguez-Borrego, M., Fabbian, F., & Jesus Lopez-Soto, P. (2020). Individual circadian preference, shift work, and risk of medication errors: A cross-sectional web survey among Italian midwives. *International Journal of Environmental Research and Public Health*, *17*(16), 5810. https://doi.org/10.3390/ijerph17165810

Chrusciel, J., Fontaine, X., Devillard, A., Cordonnier, A., Kanagaratnam, L., Laplanche, D., & Sanchez, S. (2019). Impact of the implementation of a fast-track on emergency department length of stay and quality of care indicators in the Champagne-Ardenne region: A before–after study. *BMJ Open*, *9*(6), 1–8. https://doi.org/10.1136/bmjopen-2018-026200

Cohen, R., Ning, S., Yan, M. T. S., & Callum, J. (2019). Transfusion safety: The nature and outcomes of errors in patient registration. *Transfusion Medicine Reviews*, *33*(2), 78–83. https://doi.org/10.1016/j.tmrv.2018.11.004

Crew, D., Furlow, P., & Houser, S. H. (2021.). Overcoming challenges of merging multiple patient identification and matching systems: A case study. *Perspectives In Health Information Management*, *18*.https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7883361/

Dooling, J., Fernandes, L. M., Kirby, A., Landsbach, G., Lusk, K., Munns, M., Noreen, N., O'Connor, M., & Patten, M. (2016). Survey: Patient matching problems routine in healthcare. *Journal of AHIMA*.

Edmonds, W., & Kennedy, T. (2017). *Quantitative methods for nonexperimental research: An applied guide to research designs*. SAGE Publications. https://doi.org/10.4135/9781071802779

Farmer, A., & Farmer, G. (2021). *Research methods for social work*. SAGE Publications, Inc. https://dx.doi.org/10.4135/9781071878873.n13

Flynn, D., Francis, R., Robalino, S., Lally, J., Snooks, H., Rodgers, H., & Price, C. (2017). A review of enhanced paramedic roles during and after hospital handover of stroke, myocardial infarction and trauma patients. *BMC Emergency Medicine*, *17*(5), 1–13. https://doi.org/10.1186/s12873-017-0118-5

Freeman, M., Robinson, S., & Scholtes, S. (2017*). Gatekeeping under congestion: An empirical study of referral errors in the emergency department* (INSEAD Working Paper No. 2020/09/TOM). *Pharmaceutical Science Research Network*. https://doi.org/10.2139/ssrn.3036999

Garza, M., Williams, T., Myneni, S., Fenton, S., Ounpraseuth, S., Hu, Z., Lee, J., Snowden, J., Zozus, M., Walden, A., Simon, A., McClaskey, B., Sanders, S. Beauman, S., Ford, S., Mallock, L, Wilson, A., Devlin, L. & Young, L. (2022). Measuring and controlling medical record abstraction (MRA) error rates in an observational study. *BMC Medical Research Methodology, 22*(227). https://doi.org/10.1186/s12874-022-01705-7

Gasperini, B., Pierri, F., Espinosa, E., Fazi, A., Maracchini, G., & Cherubini, A. (2020). Is the fast-track process efficient and safe for older adults admitted to the emergency department? *BMC Geriatrics*, *20*(1), 1–6. https://doi.org/10.1186/s12877-020-01536-5

Gyamfi, A., Mensah, K. A., Oduro, G., Donkor, P., & Mock, C. N. (2017). Barriers and facilitators to electronic medical records usage in the emergency centre at Komfo Anokye Teaching Hospital, Kumasi-Ghana. *African Journal of Emergency Medicine*, *7*(4), 177–182. https://doi.org/10.1016/j.afjem.2017.05.002

Harris, S., & Houser, S. (2018). Double trouble: Using health informatics to tackle duplicate medical record issues. *Journal of AHIMA*, *89*(8), 20–23.

Hsieh, M., Wang, E. M., Lee, W., Li, L., Hsieh, C., Tsai, W., & Liu, T. (2018). Application HFACS, fuzzy TOPSIS and AHP for identifying important human error factors in emergency departments in Taiwan. *International Journal of Industrial Ergonomics*, *67*, 171–179. https://doi.org/10.1016/j.ergon.2018.05.004

Hunter, J., Porter, M., & Williams, B. (2020). Towards a theoretical framework for situational awareness in paramedicine. *Safety Science*, *122*. https://doi.org/10.1016/j.ssci.2019.104528

Hwang, C. E., Lipman, G. S., & Kane, M. (2015). Effect of an emergency department fast track on Gress-Ganey patient satisfaction scores. *Western Journal of Emergency Medicine*, *16*(1), 34–38. https://doi.org/10.5811/westjem.2014.11.21768

Institute for Healthcare Improvement. (2020). *ED fast track criteria*. http://www.ihi.org/resources/Pages/Tools/EDFastTrackTool.aspx

Just, H., Marc, D., Munns, M., & Sandefer, R. (2016). Why patient matching is a challenge: Research on master patient index data discrepancies in key identifying fields. *Perspectives in Health Information Management*,*13*(1), 1–20. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4832129/

Khunlertkit, A., Dorissaint, L., Chen, A., Paine, L., & Pronovost, P. J. (2021). Reducing and sustaining duplicate medical record creation by usability testing and system redesign. *Journal of Patient Safety*, *17*(7), 1–7. https://doi.org/10.1097/pts.0000000000000434

Khunlertkit, A., & Paine, L. (2015). A human factors approach for root cause analysis: A case of duplicate medical record number. *Proceedings of the International Symposium on Human Factors and Ergonomics in Health Care*, *4*(1), 156–161. https://doi.org/10.1177/2327857915041022

King, D., Vakkalanka, P., Junker, C., Harland, K., & Nugent, A. (2020). Emergency department overcrowding lowers patient satisfaction scores. *Journal of the Society for Academic Emergency Medicine, 28*(3), https://doi.org/10.1111/acem.14046

Knapp, H. (2018). *Intermediate statistics using SPSS.* SAGE Publications. https://doi.org/10.4135/9781071802625

Kraemer, H., & Blasey, C. (2016). *General concepts. How many subjects?* SAGE Publications. https://doi.org/10.4135/9781483398761

Landsbach, G. (2016). Study analyzes causes and consequences of patient overlay errors.

*Journal of AHIMA*, *87*(9), 40–43.

Larouzee, J., & Le Coze, J. C. (2020). Good and bad reasons: The Swiss cheese model and its critics. *Safety Science*, *126*. https://doi.org/10.1016/j.ssci.2020.104660

Lee, S. Y., Chinnam, R. B., Dalkiran, E., Krupp, S., & Nauss, M. (2020). Prediction of emergency department patient disposition decision for proactive resource allocation for admission. *Health Care Management Science*, *23*(3), 339–359. https://doi.org/10.1007/s10729-019-09496-y

Leventhal, E. L., & Schreyer, K. E. (2020). Information management in the emergency department. *ER Clinics, 38*(3), 681–691. https://doi.org/10.1016/j.emc.2020.03.004

Leviatan, I., Oberman, B., Zimlichman, E., & Stein, G. Y. (2020). Associations of physicians' prescribing experience, work hours, and workload with prescription errors. *Journal of the American Medical Informatics Association*, *00*(0), 1–7. https://doi.org/10.1093/jamia/ocaa219

Lintz, J. (2018). A qualitative study of master patient index record challenges from health information management professionals' perspectives. *Perspectives in Health Information Management,* 1-18.

Lippi, G., Mattiuzzi, C., Bovo, C., & Favaloro, E. J. (2017). Managing the patient identification crisis in healthcare and laboratory medicine. *Clinical Biochemistry*, *50*(10–11), 605–611. https://doi.org/10.1016/j.clinbiochem.2017.02.004

Lozano-Lozano, J. A., Chacon-Moscoso, S., Sanduvete-Chaves, S., & Holgado-Tello, F. P. (2021). Work climate scale in emergency services: Abridged version.

*International Journal of Environmental Research and Public Health Article Public Health*, *18*(12), 6495. https://doi.org/10.3390/ijerph18126495

Lusk, K. (2015). A decade of standardization: Data integrity as a foundation for trustworthiness of clinical information. *Journal of AHIMA*, *86*(10), 54–57.

Manias, E., Cranswick, N., Newall, F., Rosenfeld, E., Weiner, C., Williams, A., Wong, I. C. K., Borrott, N., Lai, J., & Kinney, S. (2019). Medication error trends and effects of person-related, environment-related and communication-related factors on medication errors in a paediatric hospital. *Journal of Paediatrics and Child Health*, *55*(3), 320–326. https://doi.org/10.1111/JPC.14193

Martin, B. M. (2016). Bringing HIM front and center for master data management. *Journal of AHIMA*, *87*(3), 6.

McCoy, A., Wright, A., Kahn, M., Shapiro, J., Bernstarn, E., & Sittig, D. (2013). Matching identifiers in electronic health records: Implications for duplicate records and patient safety. *BMJ Quality & Safety*, *22*, 219–224. https://doi.org/10.1136/bmjqs-2012-001419

McGregor, S. (2018). *Understanding and evaluating research: A critical guide*. SAGE Publications. https://doi.org/10.4135/9781071802656

Morgan, D. (2014). *Integrating qualitative and quantitative methods*. SAGE Publications. https://doi.org/10.4135/9781544304533

Nelson, M. (2015). Keys to help solve patient data matching. *Journal of AHIMA*, *86*(8), 28–30.

Osborne, J. (2017). *Regression & linear modeling*. SAGE Publications. https://doi.org/10.4135/9781071802724

Petaschnick, J. (2017). The high cost of patient identification errors [Editorial]. *The Receivables Report*, *6*(2).

Prints, M., Fishbein, D., Arnold, R., Stander, E., Miller, K., Kim, T., & Capan, M. (2020). Understanding the perception of workload in the emergency department and its impact on medical decision-making. *The American Journal of Emergency Medicine*, *2*(38), 397–399. https://doi.org/10.1016/j.ajem.2019.07.021

Qian, S., Munyisia, E., Reid, D., Hailey, D., Pados, J., & Yu, P. (2020). Trend in data errors after the implementation of an electronic medical record system: A longitudinal study in an Australian regional drug and alcohol service. *International Journal of Medical Informatics*, *144*. https://doi.org/10.1016/j.ijmedinf.2020.104292

Quattrini, V., & Swan, B. (2019). Evaluating triage practices in emergency department fast tracks. *International Journal of Nursing and Health Care Research*, *173.* https://doi.org/10.29011/IJNHR-173.1000673

Reason, J. (2000). Human error: Models and management. *British Medical Journal*, *320*(7237), 768–770. https://doi.org/10.1136/bmj.320.7237.768

Rogers, P., Oster, A., & Wang, D. (2017). Fast track in Calgary hospitals: Measures for quality improvement. *Canadian Journal for Emergency* Management, *19*(1), 114–115. https://doi.org/10.1017/cem.2017.310

Sauer, B. (n.d.). *The role of the patient registrar and registration reimagined*. National

Association of Healthcare Access Management. http://naham.org/page/ConnectionsPatientRegistrar

Shen, X., & Wang, X. (2015). Improving the health-care delivery process at hospital emergency services by a better use of inpatient bed information. *Electronic Commerce Research and Applications*, *14*(1), 14–22. https://doi.org/10.1016/j.elerap.2014.10.008

Spencer, S., Stephens, K., Swanson-Biearman, B., & Whiteman, K. (2019). Health care provider in triage to improve outcomes. *Journal of Emergency Nursing*, *45*(5), 561–566. https://doi.org/10.1016/j.jen.2019.01.008

Toepoel, V. (2016). *Doing surveys online*. SAGE Publications. https://doi.org/10.4135/9781473967243

Trovó, S. A., Cucolo, D. F., & Perroca, M. G. (2020). Time and quality of admissions: nursing workload. *Revista Brasileira de Enfermagem*, *73*(5). https://doi.org/10.1590/0034-7167-2019-0267

Vanbrabant, L., Braekers, K., Ramaekers, K., & Van Nieuwenhuyse, I. (2019). Simulation of emergency department operations: A comprehensive review of KPIs and operational improvements. *Computers and Industrial Engineering*, *131*, 356–381. https://doi.org/10.1016/j.cie.2019.03.025

Wagner, W., & Gillespie, B. (2019). *Using and interpreting statistics in the social, behavioral, and health sciences*. SAGE Publications. https://doi.org/10.4135/9781071814284

Waldenburger, A., Nasseh, D., & Stausberg, J. (2016). Detecting duplicates at hospital admission: Comparison of deterministic and probabilistic record linkage. *Studies in Health Technology and Informatics*, *226*, 135–138. https://doi.org/10.3233/978-1-61499-664-4-135

Ward, M. J., Froehle, C. M., Hart, K. W., & Lindsell, C. J. (2013). Operational data integrity during electronic health record implementation in the ED. *American Journal of Emergency Medicine*, *31*(7), 1029–1033. https://doi.org/10.1016/j.ajem.2013.03.027

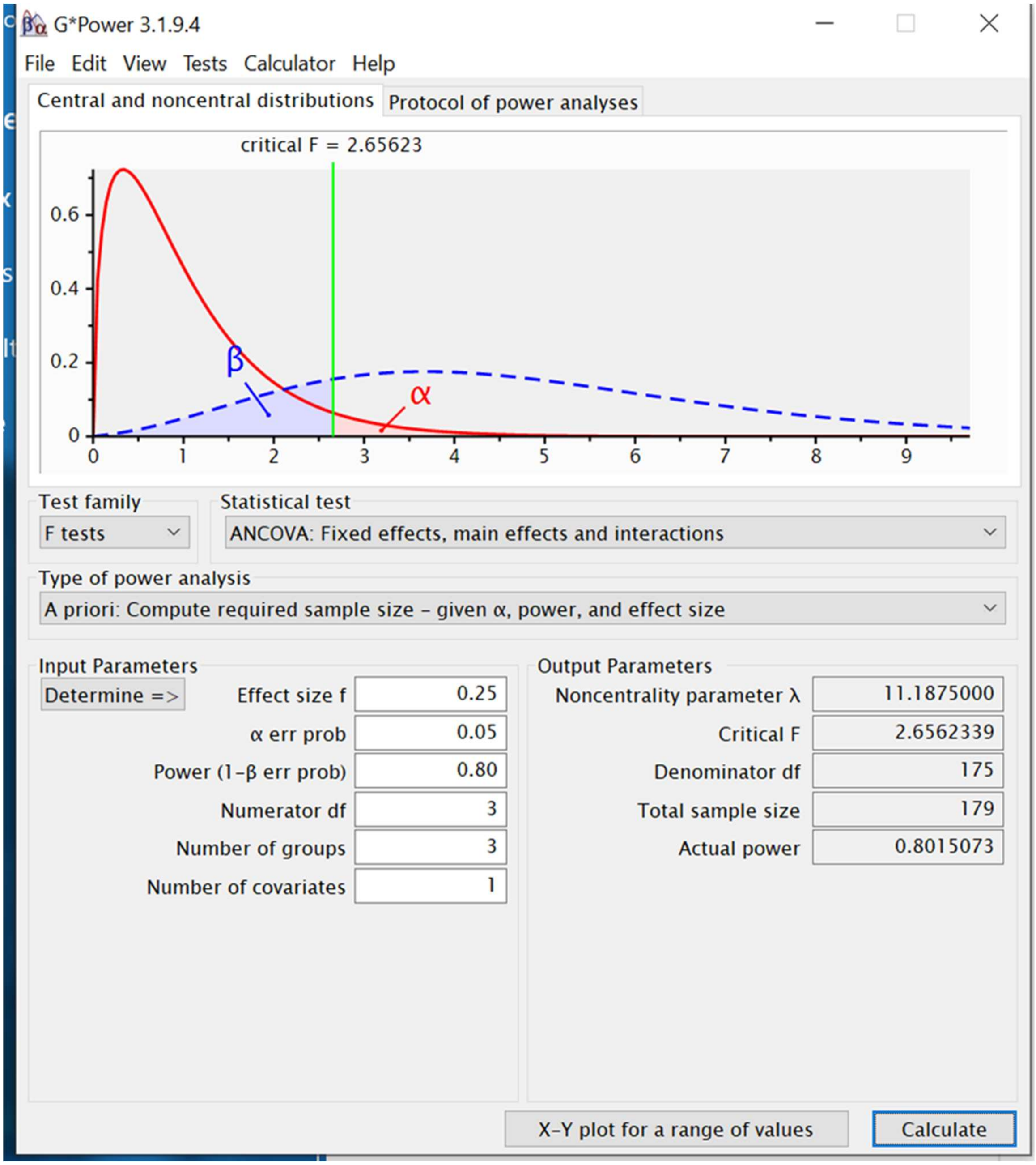
Watson, D. S. (2016). *Reducing surgery scheduling errors* [Doctoral dissertation, Washington State University]. ProQuest Dissertations and Theses Global.

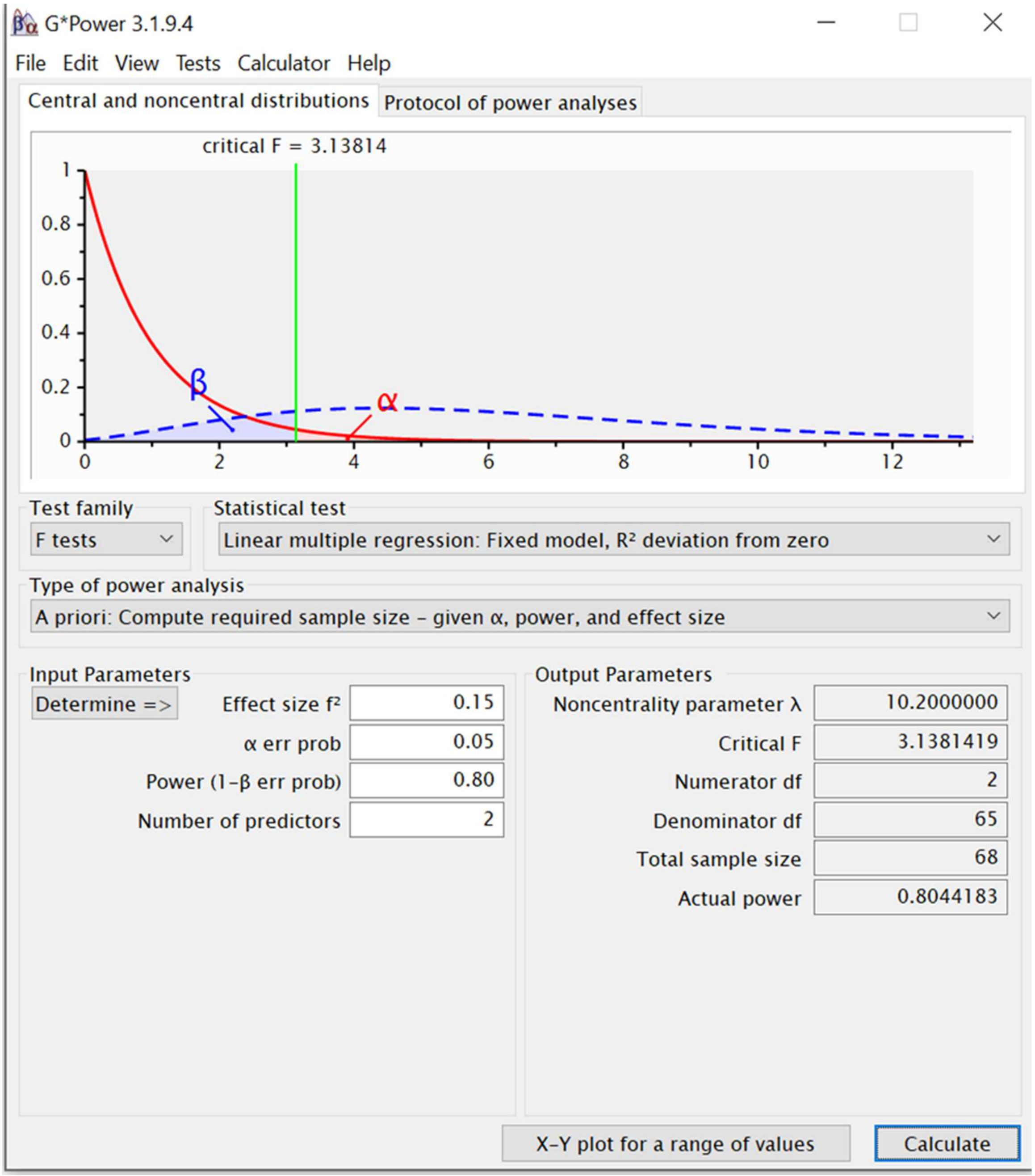
Weigl, M., Müller, A., Holland, S., Wedel, S., & Woloshynowych, M. (2016). Work conditions, mental workload and patient care quality: A multisource study in the emergency department. *BMJ Quality and Safety*, *25*(7), 499–508. https://doi.org/10.1136/bmjqs-2014-003744

Wilson, J., & Joye, S. (2017). *Research methods and statistics*. SAGE Publications. https://doi.org/10.4135/9781071802717

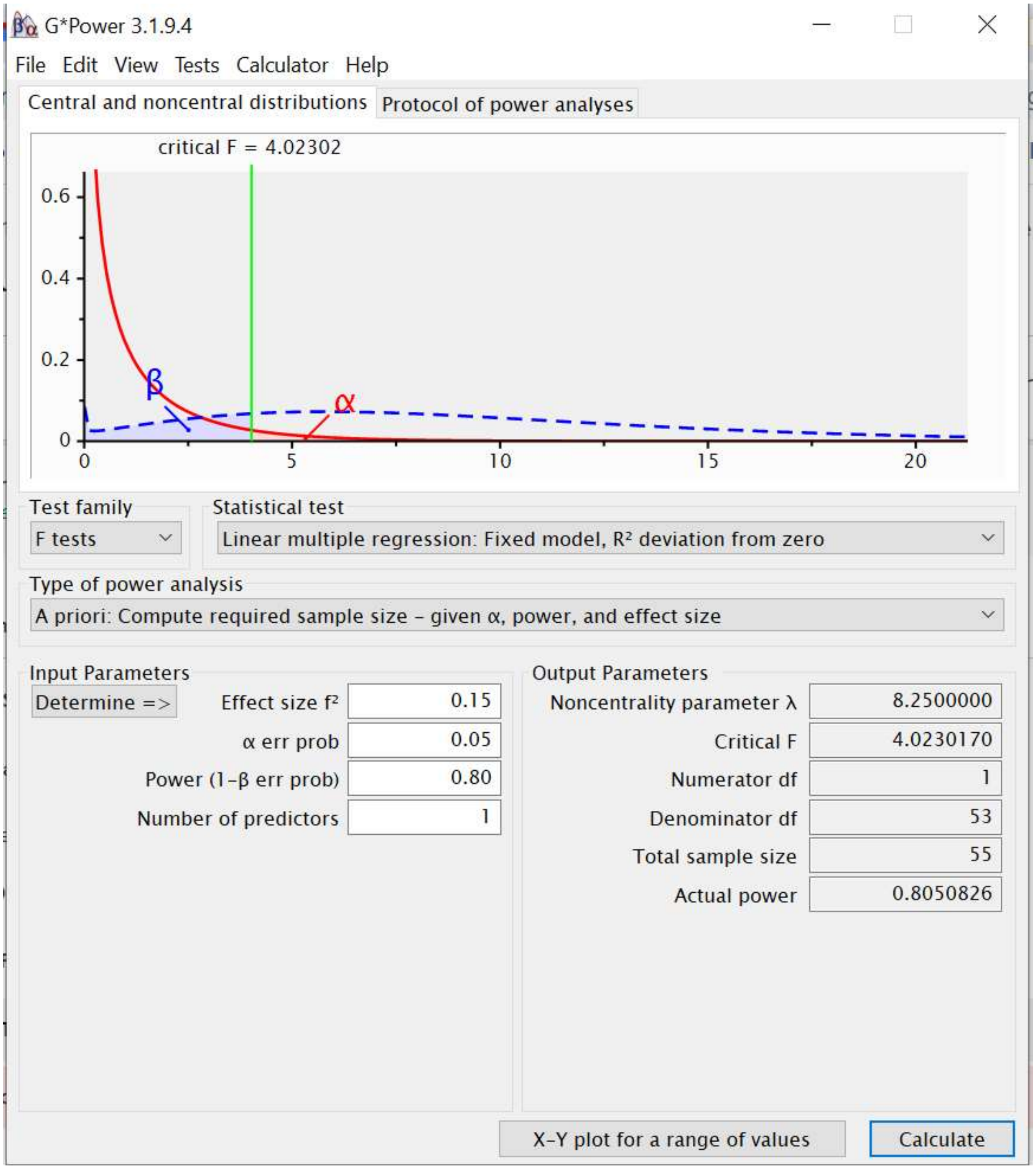
Zhao, J. (2018). *Identification of master patient index (MPI) record challenges from healthcare professionals' perspectives* [Doctoral dissertation, Central Michigan University]. ProQuest Dissertations & Theses Global.

Appendix A: G Power Sample Size Calculation





G*Power 3.1.9.4
File Edit View Tests Calculator Help
Central and noncentral distributions
Protocol of power analyses
critical F = 3.13814
β
α
Test family
F tests
Statistical test
Linear multiple regression: Fixed model, R² deviation from zero
Type of power analysis
A priori: Compute required sample size – given α, power, and effect size
Input Parameters
Determine =>
Effect size f² 0.15
α err prob 0.05
Power (1-β err prob) 0.80
Number of predictors 2
Output Parameters
Noncentrality parameter λ 10.2000000
Critical F 3.1381419
Numerator df 2
Denominator df 65
Total sample size 68
Actual power 0.8044183
X-Y plot for a range of values
Calculate


G*Power 3.1.9.4
File Edit View Tests Calculator Help
Central and noncentral distributions
Protocol of power analyses
critical F = 4.02302
β
α
Test family
F tests
Statistical test
Linear multiple regression: Fixed model, R² deviation from zero
Type of power analysis
A priori: Compute required sample size – given α, power, and effect size
Input Parameters
Determine =>
Effect size f² 0.15
α err prob 0.05
Power (1-β err prob) 0.80
Number of predictors 1
Output Parameters
Noncentrality parameter λ 8.2500000
Critical F 4.0230170
Numerator df 1
Denominator df 53
Total sample size 55
Actual power 0.8050826
X-Y plot for a range of values
Calculate

Appendix B: Research Question 1—ANCOVA Assumptions

**Figure B1**

*Scatterplot of Errors by Admissions by Shift*

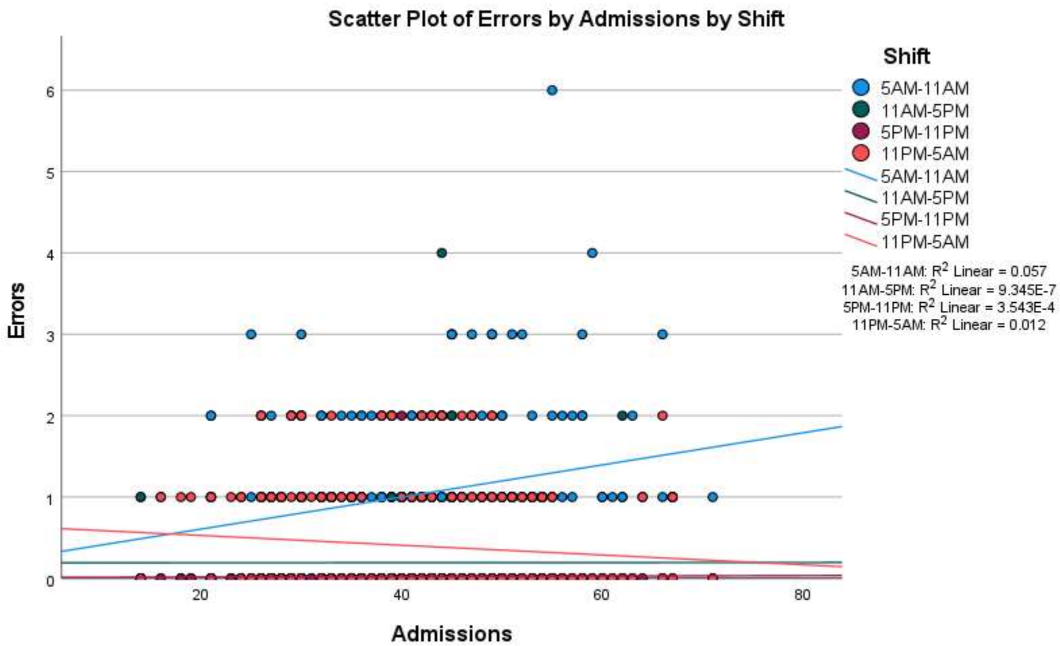


**Table B1**

*Homogeneity of Regression Slopes*

| Tests of Between-Subjects Effects (Dependent Variable) | | | | | |
|---|---|---|---|---|---|
| Source | Type 3 sum of squares | *df* | Mean square | *F* | Sig. |
| Corrected model | 136.270[a] | 7 | 19.467 | 51.399 | 0.000 |
| Intercept | 4.380 | 1 | 4.380 | 11.563 | 0.001 |
| Shift | 3.408 | 3 | 1.136 | 2.999 | 0.030 |
| Admissions | 1.398 | 1 | 1.398 | 3.691 | 0.055 |
| Shift * admissions | 10.641 | 3 | 3.547 | 9.366 | <0.001 |
| Error | 325.721 | 860 | 0.379 | | |
| Total | 608.000 | 868 | | | |
| Corrected total | 461.991 | 867 | | | |

Appendix C: Research Question 2-3— Simple Linear Regression Assumptions

**Figure C1**

*Scatterplot Showing Linearity*

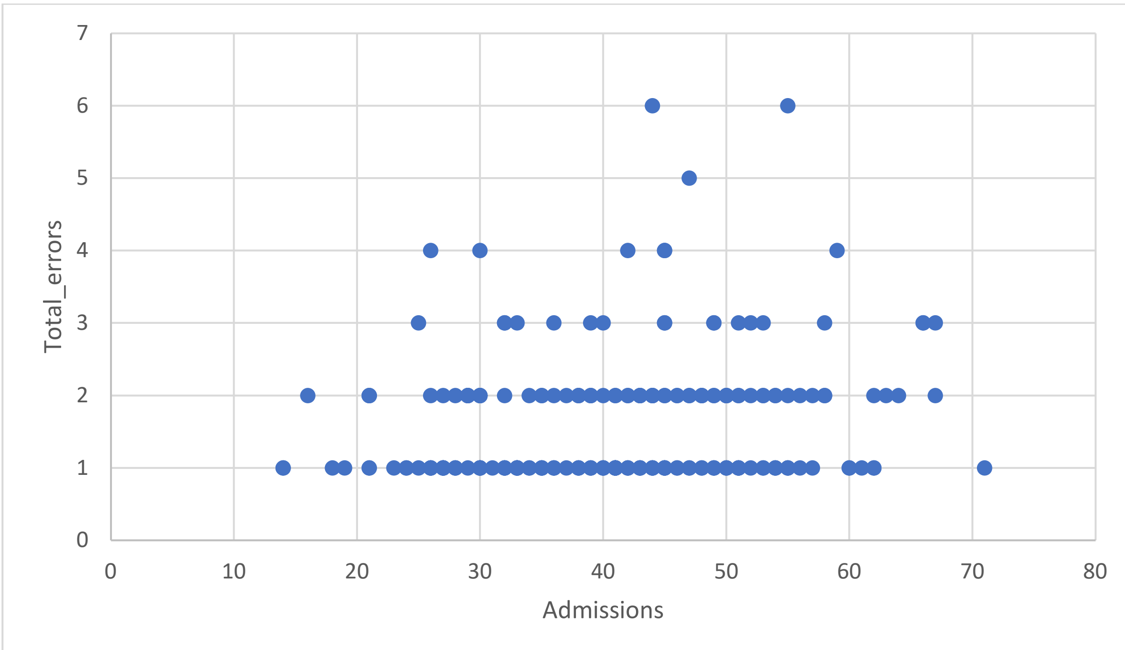


**Table C1**

*Standardized Residuals Greater Than [3]*

| Casewise diagnostics [a] | | | | |
|---|---|---|---|---|
| Case number | Standard residual | Total errors | Predicted value | Residual |
| 74 | 3.703 | 5 | 1.72 | 3.277 |
| 109 | 4.881 | 6 | 1.68 | 4.319 |
| 198 | 4.706 | 6 | 1.84 | 4.165 |

**Figure C2**

*Scatterplot Showing Homoscedasticity*

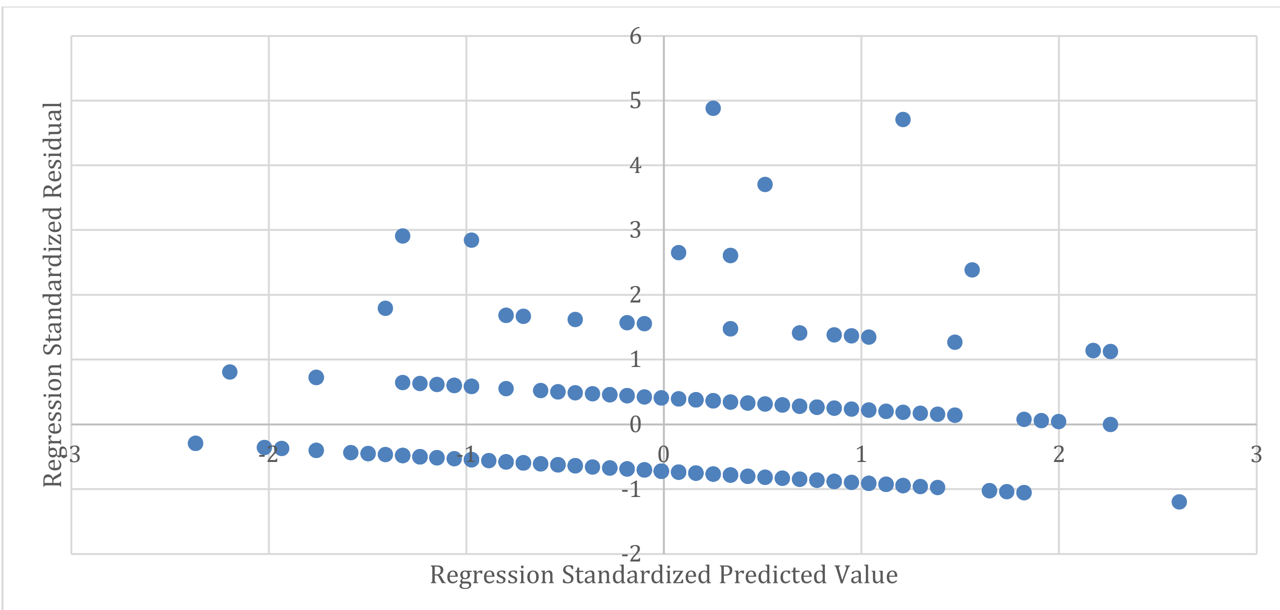


**Figure C3**

*Histogram & P-P-Plot*