THE IMPACT OF COMPUTERIZED PROVIDER ORDER ENTRY IMPLEMENTATION ON MORTALITY AND LENGTH OF STAY IN A LARGE ACADEMIC HOSPITAL

by

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ABSTRACT

Computerized provider order entry (CPOE) is a component of electronic health records (EHR) that has been touted as a crucial means to support healthcare quality and efficiency. The costs of EHR implementation can be staggeringly high, and little literature exists to verify the hypothesized benefits of CPOE and EHRs. The purpose of this study, based on Coyle and Battle's adaptation of the classic Donabedian quality improvement framework, was to evaluate system-wide outcomes after CPOE implementation in a large academic setting. The specific aims were to describe the association between CPOE implementation and (1) mortality rate and (2) length of stay (LOS), controlling statistically for antecedent, structure, and process variables.

The study used hierarchical linear modeling to analyze clinical and administrative data from 2.5 years before and 2.5 years after CPOE implementation. Aim 1 analysis included 104,153 hospital visits and aim 2 analysis included 89,818 visits. Two models were created for each analysis, (a) a model with individual patient care units as the unit of analysis and (b) a model with units aggregated by type.

LOS decreased 0.9 days per visit in all models. Mortality decreased 1 to 4 deaths per 1000 visits, depending on the model; or 54 to 216 patient lives saved in the postimplementation period. Significant antecedents were patient demographics, insurance type, and scheduled versus emergency admission; structure variables included patient care unit, private room, and palliative care; and process variables included nursing care

hours and the number of orders placed. Mortality models were variable by patient care unit, and strongly influenced by confounders such as rapid response team or code activation, suggesting the importance for future studies to account for those influences.

CPOE was statistically associated with clinically significant improvements in the system-wide outcomes. Controlling statistically for antecedent, structure, and process variables, the analysis found that after the implementation of CPOE, there was a decrease in mortality and LOS. Future studies need to determine how CPOE implementation impacts nursing performance and how CPOE influences the effect of new physician resident arrival on patient outcomes.

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GLOSSARY

ADT – Admit Discharge Transfer. The abbreviation used to describe the electronic system that captures patient location through the hospital stay.

Atomic level data – Database terminology describing data that are in the smallest meaningful form. For example, blood pressure is not atomic level data because it contains two components, the systolic and the diastolic values. Systolic blood pressure is considered atomic level data because the data cannot be further decomposed without losing meaning.

CPOE – Computerized Provider Order Entry. Software and processes to support providers directly entering the patient orders into an EMR. Providers who are licensed to prescribe include medical doctors (MD), doctor of osteopathy (DO), nurse practitioners (NP), advanced practice nurses (APRN), and physician assistants (PA). CPOE also includes a small percentage of orders entered by registered nurses (RN) and pharmacists (Rx) and cosigned by any of the above providers.

Diagnostic Related Group (DRG) – A system that classifies patients in the inpatient setting and that forms the basis for Medicare reimbursement. DRGs are assigned based on International Classification of Diseases (ICD) codes for diagnoses and procedures, and on patient age, sex, discharge status, and comorbidities. Each DRG is related to the resources needed to treat that set of conditions in a particular type of patient. The average mix of all the DRGs in a hospital or patient care unit is called the *Case Mix Index*. A refinement of the DRG classification that is intended to represent the broader population, not just Medicare patients, and to more discretely categorize patients based on severity of illness, is called the *All Patient Refined Diagnostic Related Group* (APR-DRG).

EMAR – Electronic Medication Administration Record. The portion of the electronic medical record where nurses document medication tasks. A medication task describes the events associated with a nurse preparing, giving to a patient, and evaluating the effectiveness of prescription and nonprescription drugs.

EMR/EHR – Electronic Medical (Health) Record. The record of care received by a patient in an organization, maintained in electronic format. The EHR represent the overarching patient record and includes inpatient and outpatient visits.

Encounter – Also known as *visit*. Represents a period of time during which the patient was admitted to the hospital. Patients in an organization typically receive a medical record number or patient index number representing the person, and an encounter (or visit) number that is unique to each visit.

Health Services Research – A type of research that focuses on health care services; includes access to healthcare, costs, outcomes as well as ways to organize, manage, and deliver high-quality care, reduce errors, and improve patient safety.

Length of Stay (LOS) – And Average Length of Stay (ALOS). LOS represents the duration of an inpatient encounter. ALOS is calculated by adding the total number of inpatient hospital days and dividing by the number of encounters. This calculation is typically calculated for a hospital or patient care unit over the course of a year and is often subdivided by the DRG.

Mortality incidences – Operationalized for this study as the number of deaths per observations.

Mortality rate – The number of deaths for a given population in a specified period of time. Operationalized for this study as a simple ratio, the number of deaths per 1000 patient visits.

Standardized mortality rate/ratio – A frequently used benchmarking statistic in which the observed mortality rate is compared to the expected mortality rate in a standard or comparable population.

Order Set– A component of the electronic medical record in which a group of orders are displayed together, usually based on a procedure (e.g., hip replacement surgery) or diagnosis (e.g., community acquired pneumonia).

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CHAPTER 1

INTRODUCTION

Background

Electronic health records (EHR), particularly those with advanced functions such as computerized provider order entry (CPOE), have been a focus of national attention and policy. These technologies have been described as critical tools to reduce costs and improve healthcare quality and safety (Zlabek, Wickus, & Mathiason, 2011). The U.S. government is offering financial reimbursement to encourage hospitals and providers to adopt those technologies, and financial penalties for lack of adoption, as part of the American Recovery and Reinvestment Act enacted in 2009 (U.S. Government, 2009). Despite financial incentives, EHR adoption is staggeringly expensive and comes with unintended consequences (Ash, Sittig, Dykstra, Campbell, & Guappone, 2009). Cost estimates range from $3 million for a small hospital to $200 million or more for a large hospital (American Hospital Association [AHA], 2010). Duke University, a large academic institution, recently reported a cost of $700 million for the implementation of their new EHR system (Lewis, 2012).

Electronic Health Records (EHR) were first reported in 1965. Since then, EHR systems have evolved from simple documentation systems, to systems that include sophisticated functions supporting clinical workflow and decision making, such as computerized provider order entry (CPOE). Over the course of the last 45 years, there have been increased computer software and hardware capabilities, and commitments by software vendors to create more user-friendly graphical user interfaces and to support clinician adjustment to change; factors that promote electronic health record adoption (Poon, Blumenthal, Jaggi, Honour, & Kaushal, 2004).

Major institutions including the Institute of Medicine and the U.S. government have endorsed the use of electronic health records and computerized provider order entry as a means to improve healthcare quality (Institute of Medicine [IOM], 1999, 2001, 2012; U.S. Government, 2009). The last two decades have shown an increase in EHR and CPOE implementation, although definitions and data regarding implementation rates are conflicting. CPOE can encompass many different types of orders. A U.S. hospital survey by Jha et al. (2009) reported that computerized provider order entry, for medications only, had been implemented in just 17% of U.S. hospitals. Aarts and Koppel (2009) estimated 15% of hospitals had implemented CPOE for medications and other orders. Two years later, a 'steep increase' was noted, with 21.7% of hospitals having CPOE, but the type of orders included in the CPOE system was not noted (Terry, 2011). It is clear that the rate of adoption for computerized provider order entry, whatever definition, remains low. Possibly because of the slow rate of adoption and difficulty obtaining data (Poon et al., 2004), there are few studies that discuss outcomes of CPOE usage.

Two commonly reported organizational-level healthcare outcomes are mortality and length of stay. These metrics are frequently used as benchmarks when describing or comparing organizations. Mortality is a commonly used measure of clinical outcomes. For this study, mortality was expressed as the number of deaths in a defined population during a specified time period. Mortality rate can be examined in multiple ways, such as in-hospital mortality (number of in-hospital deaths divided by the number of admissions) versus hospital mortality inclusive of an extended time beyond the hospital stay (such as 30-day mortality, calculated as the number of deaths in-hospital or within 30 days after hospital discharge, divided by the number of admissions). Because mortality is often used as a benchmark for comparisons, mortality rate may be examined in meaningful subgroups, such as infant mortality, maternal mortality, or disease-specific mortality (World Health Organization [WHO], 2012), or may be risk-adjusted according to various methods to account for differences in the baseline population of organizations being compared (Johnson et al., 2002). The few studies published regarding the impact of CPOE on mortality reported divergent results, ranging from mortality rate increase, to no changes, to decreased mortality rate (Al-Dorzi et al., 2011; Del Beccaro, Jeffries, Eisenberg, Harry., 2006; Han et al., 2005; Keene et al., 2007; Longhurst et al., 2010).

Length of stay (LOS) is a widely used indicator of hospital performance. It is the average amount of time (usually measured in days) that a patient spends in the hospital (Oregon Association of Hospitals and Health Systems [OAHHS], 2009). While most often used as an estimate of resource utilization and efficiency (and thus as a surrogate for costs), LOS has also been used as an estimate of overall quality, particularly when adjusted for patient complexity. A study in 1997 (Thomas, Guire, & Horvat, 1997) showed patients who received lower quality care had longer risk-adjusted LOS than patients who received higher quality care, presumably because lower quality care can lead to complications that extend the length of stay. On the other hand, premature discharge (much sooner than expected) could also be associated with lower quality care. While the link between length of the hospital stay and quality is not straightforward or clear-cut, an increase in patient satisfaction and reduction in hospital costs, without major changes to health outcomes, has been seen in most studies that examined the relationship between length of stay and quality (Clarke, 1996). Length of stay has persisted as a benchmark when comparing healthcare quality across healthcare groups (Ranchoin et al., 2012). Despite being a common benchmark, few studies have reported on the impact of CPOE implementation on length of stay.

Problem Statement

Millions of dollars and large amounts of time are invested in health information technology implementations. Much of this investment seems to be based on hypothesized or expected benefits for clinical outcomes or efficiency, but research that objectively assesses the impact of CPOE implementation is scarce and has shown mixed results. Studies to date have varied widely in terms of location (hospital units included in the study), patient types, study design, variables examined, and the definition of variables.

Study Purpose

With a recent, isolated implementation of computerized provider order entry, the University of Utah Health Care had the opportunity and the responsibility to assess the impact of computerized provider order entry implementation on nationally referenced outcome measures. Many factors (covariates) have been reported as potentially associated with these outcome measures. Differences in outcomes that are associated with covariates can be controlled for in statistical models, allowing for a more precise estimate of the effect of an intervention (Bartlett, 2014). The purpose of this study was to determine the impact of CPOE implementation on mortality rate and length of stay in a large academic setting, controlling for antecedent and structural covariates reported in the literature or unique to the study context.

Significance

Hospital administrators, clinicians, information technology analysts, researchers, and patients may benefit from this study. Administrators who pay for the electronic health record stand to gain from the study, because they can use the findings as a marketing point and to reassure their patients that the institution is invested in their care. Clinicians can take pride in their participation in a large change in the process of care. Information technology analysts can learn from the data quality evaluations. Using this information, the information technology analysts can make changes to the data fields to increase data correctness, completeness, plausibility, currency, and concordance (Weiskopf & Weng, 2013). Researchers can use the design to model studies at their institution and can use the lessons learned to ensure the data are fit for use (Juran, 1974). Patients may benefit most from this study. Providing patients with data from a study performed at their hospital may empower them when making choices about their healthcare insurance and healthcare provider (Arrow, 1963).

Improving healthcare quality and reducing cost has become a high priority of healthcare reform in the United States. Informatics is crucial in tackling this challenge. A major responsibility of informatics nurse specialists and informatics researchers is to evaluate electronic health records and the impact on clinical workflows and patient outcomes (American Nurses Association [ANA], 2008; Shortliffe & Cimino, 2006). Information technology analysts and informatics researchers will gain generalizable knowledge about the effects of health IT implementation. Researchers and informaticians at other institutions can apply the study methodology to measure the impact of computerized provider order entry implementation on their patient outcomes.

Theoretical Framework

A variation of Donabedian's Structure, Process, Outcome framework was used to guide this study (Coyle & Battles, 1999). Avedis Donabedian was a medical doctor who, while researching quality assessment in the medical field, devised a framework that has become the foundation for modern quality assessment activity (Frenk, 2000). Donabedian described the components of structure, process, and outcome as key influences of healthcare quality (Donabedian, 1966). Structure describes the environment in which care takes place and includes the administrative structure, programs, resources (including personnel), and similar aspects. Process involves actions, i.e., the care that is given to patients by the staff. Outcomes are the results of care and can be measured in a variety of ways, ranging from simple dichotomous measures like mortality, to complex multi-layered expressions such as quality of life. "Outcomes, by and large, remain the ultimate validators of the effectiveness and quality of medical care" (Donabedian, 1966, p. 694).

Coyle and Battles (1999) adapted Donabedian's model by adding antecedents. Antecedents are the characteristics that patients bring to their hospital stay and are partitioned into patient factors and environmental factors. *Patient factors* include personal characteristics such as "genetics, socio-demographics, health habits, beliefs and attitudes and preferences" (Coyle & Battles, p. 7). *Environmental factors* are "cultural, social, political, personal, physical or related to health professions" (Coyle & Battles, p. 7). The original pictorial representation of Coyle and Battles' model was a flat, two-dimensional, linear process. The Agency for Healthcare Research and Quality (Agency for Healthcare Research and Quality [AHRQ], 2012) adjusted the graphical representation by representing structure as a three-dimensional figure with processes running through it, to emphasize that processes and structure influence each other.

Operationalization of Theoretical Framework

The theoretical framework illustrates the relationship between variables that have been reported in the literature as potentially influential on the outcomes of CPOE implementation, as shown in Figure 1.1. Structure components represent the system and the healthcare setting (Coyle & Battles, 1999). *Structure* items included in this study were private room versus semiprivate room (facility characteristics), patient care nursing hours (personnel), and patient care unit. Palliative care status was categorized as a structural component because it was assigned during the visit, and influenced care decisions.

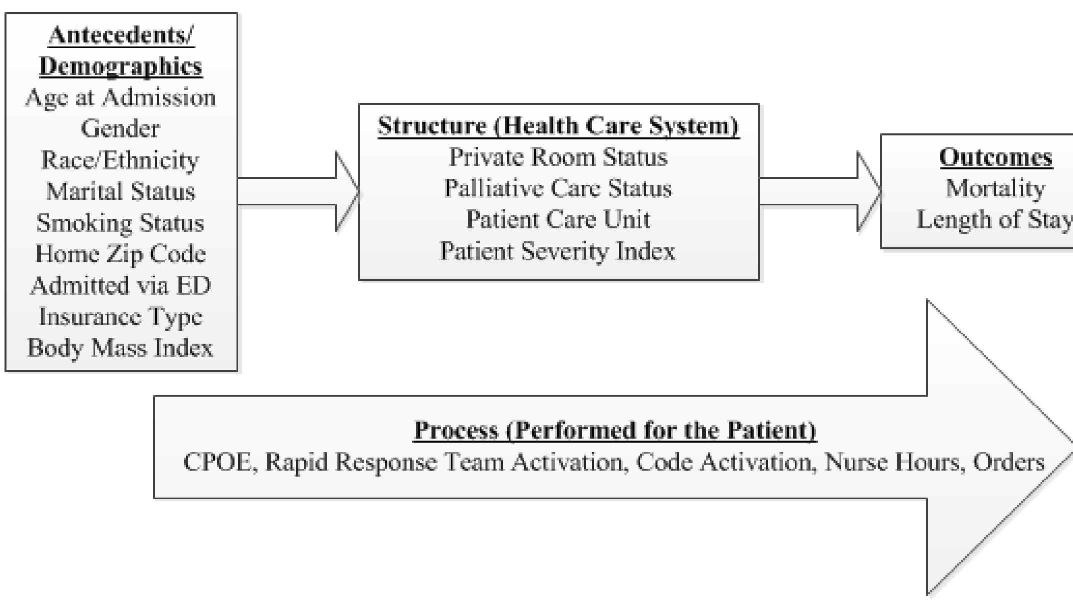

Figure 1.1 – Theoretical framework as operationalized for data extraction

Some items could be categorized as either structure or process. Rapid response team activation and code activation were categorized as process for this study, because they represent actions taken by the clinicians. These variables could also have been considered structure because having a rapid response team or code team is part of the hospital personnel structure. Computerized provider order entry (CPOE) was the primary independent variable for this study. CPOE could be considered as either a structural (the software) or process (clinician use of the software) component. Pragmatically, whether a variable was categorized as structure or process did not influence the study in any way.

Donabedian noted that outcomes could be either clinical outcomes or indicators of hospital performance (Coyle & Battles, 1999). For this study, the outcomes were mortality rate (a clinical outcome) and the average length of stay (a performance outcome).

Categorizing variables reported in the literature according to Coyle and Battles adaptation of Donabedian's framework (Coyle & Battles, 1999) guided the data extraction request, helping to define and identify desired data elements in the clinical and administrative databases. All categorized variables were extracted, although subsequent data quality evaluations necessitated the elimination of some variables from final analyses. The conceptual framework categorization also supported statistical analyses and interpretation by suggesting meaningful variable subsets, making the complex analysis more manageable.

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CHAPTER 2

REVIEW OF THE LITERATURE

The literature review begins with a brief overview of health services research and explains why this study should be considered as a form of health services research. Study context is provided through a brief history of electronic health records and computerized provider order entry, in general and then specifically at the University of Utah hospital, while considering the political climate related to EHRs and CPOE. The remainder of the literature review is guided by the components of the theoretical framework. The independent variable, computerized provider order entry (CPOE), is discussed as well as the outcome measures of mortality and length of stay. Finally, the antecedents, structure, and process variables relevant to this study are examined.

Heath Services Research

Health services research has a broad definition that has evolved over time. Flook and Sanazaro (1973) started with a definition that was specific to hospitals and was concerned with staffing issues, and financial and utilization components. The Institute of Medicine (1994) later refined the definition, aligning it with Donabedian's (1966) structure, process, and outcome model. AcademyHealth (2000), the professional organization for health services research, incorporates the Institute of Medicine definition and dovetails with the conceptual framework used in this study by encompassing antecedents, structure, process and outcomes, while expanding the definition to include hospital patients, clinic patients, as well as population components such as families and communities. AcademyHealth defined health services research as the scientific field that studies "social factors, financing systems, organizational structures and processes, health technologies, and personal behaviors affect access to health care, the quality and cost of health care, and ultimately our health and well-being" (AcademyHealth, 2000, para.1). Health services research methods often include analysis of data collected from surveys, and secondary analysis of data collected for clinical and other purposes (AcademyHealth, 2000). The Agency for Healthcare Research and Quality noted that the field examines health care access, costs, and outcomes; ways to organize and manage care; and methods to reduce errors and improve safety (AHRQ, 2009).

This study met the definition of health services research. The study included components described by the various authors and agencies who defined health services research. The study examined health services from a system perspective by evaluating data collected for clinical purposes in an electronic health record.

Electronic Medical Records

Historically, medical records were documented in a paper chart that was kept at the nurse's station, at the bedside, or in some other, possibly unknown, location. Additional charts were kept in doctors' offices and clinics. Often, the data on these multiple charts overlapped, but at the same time, there were also gaps, creating an incomplete picture of the patient's history, medication regimen, and treatments. Numerous problems have been reported with paper records, including lack of access to the record, incompleteness, illegible handwriting, and disorganization (Hersch, 1995).

An Electronic Health Record (EHR) was first used in a hospital in 1965 and was introduced into a patient care unit in 1971 at El Camino Hospital in Mountain View, California (Staggers, Thompson, & Snyder-Halpern, 2001), representing the beginning of the era of storing patient data in an electronic chart. El Camino Hospital implemented a system that included physician orders, lab results, and nursing documentation (Barrett, Barnum, Gordon, & Pesut, 1975).

Over the last 40 years, increased computer software and hardware capabilities, commitments by software vendors to create user friendly software, and the adjustment to change by clinicians have promoted electronic medical record adoption. Legislation and financial incentives such as the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 have accelerated the adoption rate. EHR adoption was up to 59% of acute care hospitals in 2013, an increase of 34% over the 2012 adoption rate (Charles, Gabriel, & Furukawa, 2014).

Documented EHR benefits include decreasing turn-around times from laboratory order placement to result notification (Mekhjian et al., 2002), decreasing costs and length of stay (Tierney, Miller, & Overhage, 1993), improving patient safety (Evans, Pestotnik, Classen, & Burke, 1999), decreasing redundant care (Bates et al., 1999), increasing nurse charting efficiency (Wong et al., 2003), decreasing time spent performing chart reviews (Kerr et al., 2002), and creating data repositories that can be used for research (Safran et al., 2007). EHR drawbacks include increased data entry time; increased hardware, software, training, and maintenance costs (Menachemi & Brooks, 2006; Sidorov, 2006); and changes in workflow that require clinicians to spend time and energy adjusting to the new system (Overhage, Perkins, Tierney, & McDonald, 2001).

Electronic Health Records at the University of Utah

The University of Utah hospital started designing and building an electronic health record prior to 1994. In 1997, the University abandoned building its own system and purchased an electronic health record system from a vendor called Oacis. Two years later, Oacis was purchased by another company and the EHR implementation at the University of Utah could not be realized. In 2001, a search committee was convened to explore the purchase of an EHR system from a different vendor. After a year’s worth of demonstrations and deliberations, the committee selected the Cerner electronic health record. One of the deciding factors was that the University of Utah had installed the Cerner Inpatient Pharmacy system in 2001. The Cerner product focused on the inpatient setting while the runner-up system, Epic, focused on the outpatient setting.

As is typical for most vendor-supplied electronic health records, the software was customized for the local setting and implemented in stages. In 2003, the University of Utah implemented the "results review" portion of the Cerner electronic health record. Results review included discrete, structured data for patient demographics, allergies, problems, and diagnoses, and laboratory results; and the system linked to text documents. Allergies, problems, and diagnoses could be entered into the inpatient electronic medical record by clinicians as discrete values, but that form of data entry was not widely used. Instead, providers dictated allergies, problems, and diagnoses that were then stored in the health record as text documents. Lab results were sent to the inpatient electronic medical record via an interface from ARUP Laboratory’s electronic system (also a Cerner product). Many other dictated notes, including history and physical, operative notes, and radiology reports, were also deposited into the electronic health record via electronic interfaces from their respective non-Cerner systems. The majority of records were text notes and documents.

This work comprised the first portion of the inpatient electronic health record at the University of Utah hospital. Multiple software upgrades followed, along with implementation of scanning for the University Orthopaedic Center in March 2007. In 2007, the hospital planned to implement CPOE for University Hospital, Huntsman Cancer Institute, and the University of Utah Neuropsychiatric Institute.

After two unexpected events in which the EHR was unavailable for extended periods of time, the hospital administration postponed CPOE implementation. Although the CPOE implementation was postponed, the hospitals implemented nursing documentation in June 2007. Nursing documentation included charting medications on the electronic medication administration record (EMAR), and documenting nursing assessments and patient events. Most of the nursing documentation was built to store the data as discrete (atomic level) data. Having discrete data was an important milestone, because it allowed the data to be amenable to computer processing; providing a way to measure patient symptoms and outcomes.

In April 2009, after improving the network infrastructure and readying the institution for change, CPOE was successfully implemented in most inpatient areas at all three hospitals. The burn unit implemented CPOE first, followed by the remainder of the patient care units in all three hospitals over a 6-week period. CPOE was an isolated implementation, with no other electronic health record functionality being implemented at the same time. This provided a unique opportunity to evaluate the impact of CPOE implementation.

Political Influences on EHR Adoption

Electronic health record (EHR) design and the rush to implement EHR adoption have been shaped by the U.S. political climate. The Institute of Medicine (1999) brought dramatic attention to the number of preventable deaths in the U.S. The IOM suggested strategies to increase patient safety, one of them being the implementation of computerized provider order entry. The 2001 Institute of Medicine report stated "Information technology (IT) must play a central role in the redesign of the healthcare system if a substantial improvement in quality is to be achieved" (IOM, 2001, p. 165). The RAND Corporation projected billions of dollars in savings with widespread electronic health record implementation (Hillestad et al., 2005; Hillestad & Girosi, 2009).

In 2009, the United States government passed the American Recovery and Reinvestment Act (ARRA), an economic stimulus bill. One component of the ARRA bill was the Health Information Technology for Economic and Clinical Health (HITECH) Act, which awards financial incentives to hospitals that can verify their electronic health record meets *Meaningful Use* criteria (U.S. Government, 2009). *Meaningful Use* is a vague term. It represents both the implementation and documented use of specified aspects of electronic health records. *Meaningful Use* has been divided into three phases with each phase increasing the complexity and scope of electronic health record use. For Meaningful Use Stage I, implemented in 2011, regulations specified that electronic health records must include charting vital signs, documenting allergies in a discrete format, maintaining an active medication list, and CPOE. Stage II criteria, currently being finalized, include electronic reporting for quality measures. The U.S. government is slated to reimburse hospitals and patient care providers (to a total of at least two billion dollars) for implementing and/or adopting electronic health records to manage patient care; and conversely, hospitals will be financially penalized for failing such adoption (Health & Human Services [HHS], 2010). As a result, hospital organizations have been highly motivated toward electronic health record investment.

Electronic health record vendors have worked diligently to meet the government's specifications and obtain certification of their EHR (HHS, 2010). In addition, the vendors have had to increase the rate of development, testing, and report creation to document the indicators of meaningful use that are specified by the government. It is possible the electronic health record vendors would have eventually created similar functionality on their own, but the political climate contributed to the standardization of functionality and the aggressive timeline to document and report on patient outcomes.

Computerized Provider Order Entry

Computerized provider order entry (CPOE) is the EHR aspect that is most anticipated to support healthcare quality and safety. CPOE is both a software function and a human process. The vast majority of medication errors occur at the ordering or transcribing stage (AHRQ, 2014). CPOE supports providers' (physicians, advanced practice nurses, nurse practitioners, physician assistants, and midwives) direct entry of orders into the EHR. Historically, providers would write orders on paper or dictate orders, which were then transcribed into the patient record; a process that could take several steps between initial order and order fulfillment, and involve multiple people. The process of CPOE focuses on the provider entering his/her own order into the computer system, thus eliminating transcription errors and problems related to illegible handwriting (AHRQ, 2014). The orders are automatically routed to and acted upon by laboratory, radiology, nursing, and other staff.

CPOE became the next logical step in electronic health record implementation for a number of reasons. Clinicians have become more familiar with computers, with basic understanding of how computers, databases, and interfaces work and interconnect. In addition, clinicians have become more adept at solving their own problems (Maslove, Rizk, & Lowe, 2011), increasing the feasibility of large-scale implementation. When coupled with decision support functions such as drug-drug or drug-allergy checking, CPOE is anticipated to prevent errors by alerting providers to potential problems at the time the order is issued (AHRQ, 2014). CPOE has been credited with decreased transcription errors (Mekhjian et al., 2002), increased formulary compliance (Teich et al., 2000), and decreased lab turnaround times (Thompson, Dodek, Norena, & Dodek, 2004).

CPOE implementation was mandated as part of legislation requiring EHR adoption. However, the actual impacts of the CPOE implementation are sparsely documented and literature varies regarding whether the anticipated effects were realized in real-life settings. Mortality and length of stay are commonly used outcome variables in health services research, but the reported impact of CPOE on mortality and length of stay has been variable. The following sections describe mortality and length of stay as outcome metrics, and the relationship between those metrics and CPOE.

Mortality Rate

Mortality rate (death rate) is a traditional healthcare outcome measure. On a personal level mortality is an easy concept to understand—you are either alive or dead. From a historical and epidemiological perspective, it makes sense to track deaths (and births), especially with regards to disease and pestilence. While mortality seems like it should be easily measured, it is not that simple, because mortality rate can be calculated many ways. When a person thinks of mortality rate, it is likely s/he is thinking of the crude mortality rate. Crude mortality rate is calculated by dividing the number of deaths by the number of people in a population during a given period of time and includes every death in the population (London School of Hygiene and Tropical Medicine, 2009).

From a healthcare system or governmental standpoint, however, mortality rates are quite complex. Some of the mortality rate calculations add a fourth component. For example, mortality can be separated by age categories (e.g., deaths in children under 5 years of age), by group (e.g., maternal mortality), by cause (e.g., mortality related to the H1N1 flu epidemic), or by a specified time period (e.g., 30-day mortality or 1-year mortality). The denominator defining the population is also variable. At the hospital level, mortality could be calculated with the number of *distinct patients* over a specific time period as the population. This calculation assumes that a patient can only die once.

The calculation more commonly used in benchmarking reports is to divide the number of deaths by the number of *patient visits* for the specific time period. If a patient is admitted to the hospital three times over the course of the year, then three episodes are included in the denominator. This approach deflates the death rate, compared to the "per patient" mortality rate, if the number of patients with multiple visits during the time period is large (because the number of patients is less than the number of visits). The primary assumption with this formula is that death is an ‘event’ and a patient has an opportunity to experience that event, every time the patient is admitted to the hospital. Both calculations are used in practice.

Risk adjustment adds another layer of complexity to mortality rates. This approach is intended to help with comparisons between hospitals, by compensating for some hospitals serving an essentially younger or healthier population, and other hospitals having a population that includes traumas, complex illnesses, or chronically ill patients (Iezzoni, 1991). However, many formulas can be used to calculate risk adjustment. Depending on the formula used, results for hospital performance vary. The mathematical formula selected for risk adjustment can result in one hospital appearing to perform very well while a different calculation could reverse those results (Shahian, Wolf, Iezzoni, Kirle, & Normand, 2010). Risk adjustment is fraught with controversy and uncertainty but it is commonly used in the U.S. with both the Centers for Disease Control and Medicare reporting risk-adjusted mortality rates.

CPOE and Mortality

Mortality and computerized provider order entry have been linked in the literature, especially since Han and colleagues (2005) reported the alarming finding of an increase in mortality rate from 2.80% to 6.57% at their pediatric hospital after implementation of a commercially sold CPOE product. This article was important because of the decision to publish less than ideal results. By reporting these negative results, Han inspired other clinician/researchers to study their own computerized provider order entry implementation.

The Han et al. (2005) study gathered information for interfacility transfers for a total of 18 months: 13 months before computerized provider order entry and 5 months post computerized provider order entry implementation. They calculated unadjusted and adjusted mortality rates. Adjusted mortality rates were based on the patient severity index score, PRISM (Pediatric Risk of Mortality), a commonly used pediatric scoring system

(Pollack, Ruttimann, & Getson, 1988). Part of the negative findings in this study were likely related to overall EHR configuration and implementation factors. Workflow and processes did not support the urgency of taking care of a critically ill baby. Han's group experienced delays with patients being "admitted" into the electronic system, which had to occur before orders could be placed and medications obtained. Once the patient was entered into the electronic record, the providers had to place each order individually and enter all the details for each order. In current CPOE systems, providers can place orders as a set, and most of the details are automatically entered as default values.

Del Beccaro, Jeffries, Eisenberg, and Harry (2006) also undertook a pre- and post-CPOE study in a pediatric population. Like Han et al. (2005), they used the Pediatric Risk of Mortality (PRISM) patient severity index, although it is not clear they used the same version of this instrument. The Del Beccaro study had equal time periods for the intervention and nonintervention phases; both were 13 months. Del Beccaro and colleagues also compared the same time frames as Han et al. (2005), and found no statistical difference in mortality rates for the 13 months before and 5 months after computerized provider order entry implementation. Their study institution used order sets, order sentences, and filtering to facilitate the ordering process. The study results were statistically nonsignificant but showed a meaningful trend, with a postimplementation mortality rate decrease from 4.22% to 3.46%.

Longhurst and colleagues (2010) also focused on a pediatric population. These authors, like Han et al. (2005), used different lengths for the pre- (6 1/2 years) and post- (18 months) implementation periods, and the authors used adjusted mortality rates. Longhurst's study had nonmedication order entry implemented 2 years prior to the phasing in of medication-related CPOE, so clinicians had some familiarity with computerized order entry systems. In addition, the Longhurst et al. study included 90% of the patients in the institution, not a small subset like Han's study. They adjusted their study to account for patients who met the criteria for rapid response team activation. Longhurst used the case-mix index (CMI) as an indication of patient severity and then compared the patient's discharge diagnosis with the Child Health Corporation of America database, a clearinghouse for 42 not-for-profit tertiary pediatric hospitals, in order to generate observed versus expected, adjusted mortality rates. Longhurst's study indicated a statistically significant 20% decrease in mean monthly adjusted mortality rate. Despite the differences in the study design, these results were in direct opposition to Han's report. Items not attributed to the results in either study were the design and build of the electronic health record and the implementation style.

Keene and colleagues' (2007) study in 1999 was different from the three previously mentioned studies for a number of reasons. The Keene et al. study used different commercial medical record system (PHAMIS, later purchased by General Electric). They began implementing CPOE one unit at a time (not the whole hospital on the same day) over the course of three years. This created an environment where clinicians had up to three years of experience using CPOE by the time it was implemented in the neonatal and pediatric intensive care units. As in the Han et al. study, patients were transferred from another facility because they needed specialized care, but only 12% of the sample had been admitted via interfacility transfer compared to the entire sample in the Han et al. (2005) study, which changes the sample composition. Keene and colleagues' study was similar in that it accounted for patient severity but it did so by retrospectively coding admission diagnoses. This may have led to more consistent diagnostic coding than traditional methods but may make it difficult to compare the studies. Keene et al. used multiple regression models to account for diagnoses and demographics to determine how these components impacted the odds of mortality. Lastly, Keene's study adjusted the time periods to accommodate the unit-by-unit implementation process, noting "there were no major changes in terms of structure, administration, or staffing ratios during these times" (Keene et al. 2007, p. 2). The Keene et al. study sample size (*n* =1,291) was much smaller than the Longhurst et al. (2010) study (*n* =80,063) or the Del Beccaro et al. (2006) study (*n* =2,533), and even smaller than the Han et al. (2005) study (*n* =1,942). Keene and colleagues found an apparent but statistically nonsignificant decrease in mortality rates between the pre- and postimplementation phases.

CPOE and mortality studies have not been limited to infants and young children. Al-Dorzi et al. (2011) researched mortality in the adult intensive care unit (*n* =2,536) population from a teaching hospital in Saudi-Arabia. Like Han et al. (2005), Longhurst et al. (2010), and Keene et al. (2007), the Al-Dorzi study collected demographics and had unequal study periods (2 years pre and 1 year post computerized provider order entry implementation). They used a patient severity index called the APACHE II system, which is used exclusively in adult intensive care units. They used APACHE scores to verify that the patient populations were similar during the pre- and postimplementation periods. Unlike the other researchers, Al-Dorzi et al. included reason for admission (cardiac arrest, postoperative trauma and nonoperative trauma), comorbid conditions (categorized as liver, cardiovascular and renal), diagnostic lab values such as coagulation levels (INR), vasopressor use, and whether or not the patient needed mechanical ventilation to describe the sample. They excluded patients who became organ donors and compared four different time periods. These authors concluded there were no increases in either mortality rates or length of stay.

The four studies that examined CPOE and mortality, performed retrospective analyses of pre and post computerized provider order entry implementation and assessed similar population characteristics, including demographics and a measure of illness severity. All but Al-Dorzi et al. studied the pediatric inpatient population. Although most used different time lengths for the pre and post phases, Del Beccaro et al. intentionally replicated the original time frames of Han et al. The implementation strategies varied; the Han et al. hospital implemented the electronic medical record all on the same day while Keene et al. experienced unit by unit implementation over an extended time, and Longhurst et al. and Al-Dorzi et al. used implementation strategies that were somewhere in between. All but Han et al. used order sets. Al-Dorzi et al. added multiple comorbidity measures, including ventilator use, vasopressor use, and lab results.

Two studies (Amarasingham, Plantinga, Diener-West, Gaskin, & Powe, 2009; Miller & Tucker, 2011) investigated how electronic medical record adoption impacted mortality rate, length of stay, and cost. While not limited specifically to CPOE, both studies showed a decrease in mortality rates and cost. Although these studies used completely different designs than the studies mentioned above, they suggest a trend supporting the hypothesized benefits.

All seven studies address some of the components from Donabedian's (1966) framework, most noticeably process (computerized provider order entry implementation) and outcomes (mortality and length of stay). All the studies included antecedents but most did not use organizational variables suggested by Donabedian's structure component. Longhurst et al. (2010) included rapid response team activation and case mix index while the others included a patient severity index. However, these studies do not take into consideration other structural factors that have been linked to mortality, such as nurse staffing (Aiken et al., 2011), private rooms (Boardman & Forbes, 2011), smoking status (Centers for Disease Control and Prevention [CDC], 2002, 2004), body mass index (BMI) (Berrington de Gonzalez et al., 2010), and insurance type (Hasan, Orav, & Hicks, 2010; Spencer, Gaskin, & Roberts, 2013).

Length of Stay

Like mortality, length of stay (LOS) is a metric for health facility benchmarking (Clarke, 1996; Ranchoin et al., 2012). Average length of stay, in the inpatient venue, is the average duration of patient visits (OAHHS, 2009). For this study, length of stay was defined as the date and time the patient was admitted to the hospital, subtracted from the date and time the patient was discharged from the hospital, and represented as a decimal number (e.g., 36 hours was represented as 1.5 days). Length of stay is an indicator used by hospital administrators to reflect costs, and is used by clinicians to reflect efficiency of patient service.

CPOE and Length of Stay

Length of stay is one of the most widely used metrics for hospital performance (Clarke, 1996; Ranchoin et al., 2012). As an indication of how common this metric is, a simple electronic library search of "length of stay" returned more than 18,000 results. A search of “length of stay” and “efficiency” returned 701 results and covered a wide array of topics, including the relationship between hospital and intensive care units, the number of hospitalists at the institution and length of stay for children with common conditions, and an article asking if the poor cost more.

Unlike the voluminous general literature regarding length of stay, there is a paucity of information about length of stay in the context of CPOE. An electronic search using the terms “length of stay” and “cpoe" returned 18 publications but not all of were pertinent to this study.

Of the studies included in this literature review, Han et al. (2005) and Keene et al. (2007) included length of stay as a confounding variable. Longhurst et al. (2010), Del Beccaro et al. (2006), Al-Dorzi et al. (2011), and Amarasingham et al. (2009) included length of stay as an outcome variable. Length of stay showed no change in the Amarasingham study, while Miller and Tucker (2011) projected decreased costs based on decreased length of stay in the neonatal populations.

While the validity of using length of stay as a measure of patient outcomes or costs may be controversial, and may have different meanings for the different stakeholder in the healthcare arena, it is one of the most commonly used outcome measures. Because of its use in previous CPOE evaluations, and because it is an extremely common health services metric, length of stay was included in this study.

Antecedent Variables

Antecedents are the characteristics that patients bring with them to their inpatient stay (Coyle & Battles, 1999). A variety of antecedent factors or confounders have been reported in the literature as potentially related to mortality, length of stay, or both. Patient characteristics (antecedent *demographic factors*) measured in previous CPOE implementation studies and used in this study were the following: age at admission, gender, race and ethnicity, and marital status. Antecedent *environmental factors* reflect other influences that patients bring with them to a hospital visit. An Institute of Medicine (2002) report cited a 25% increase in mortality risk for working-age adults who are uninsured. Kronick (2009) replicated the Institute of Medicine study, but found that smoking and body mass index (BMI) had more impact on mortality rates than insurance type. The contradictory results suggested the inclusion of insurance type, smoking status, and BMI in this study.

Bottle, Jarman, and Aylin (2011) tracked month of admission, method of admission (planned versus unplanned), and source of admission. Admission month was collected in this study. Method of admission and admission source data were not directly available in the enterprise data warehouse. Instead, patients admitted via the emergency department were analyzed as a proxy for unplanned admission status.

The University of Utah serves as a trauma center for patients in eight western states. Presumably, local patients might come to the institution for routine hospital care, whereas it is more likely that patients from further geographic areas were transferred to the University if their illness was complex or required specialty service. In this study, area of residence (postal code) served as a proxy for patient geographic location.

Structure Variables

Overall, the previously reported studies were lacking in items related to structure. Four of the seven previous studies included a patient severity indicator. One included rapid response team activation. One study accounted for month of admission and analyzed seasonal variation.

Bottle, Jarman, and Aylin (2011), whose study focused on coding issues associated with tracking mortality rates, analyzed the impact of factors on hospital standardized mortality rates and recommended including or excluding certain structure items. Palliative care status at admission suggests that the patient is to receive no extraordinary measures and is more likely to pass away at the hospital (with the death representing patient preference rather than care processes). Bottle et al. (2011) pointed out that palliative care deaths are unpreventable and consequently removed palliative care patients from their mortality calculation because it "unfairly penalized" hospitals that provide palliative care on a regular basis.

Short-stay patients, who are admitted for a procedure or surgery and go home on the same day, should also not be included in the sample, as they are unlikely to have died during the course of their stay. Hospital visits less than 1 day are typically considered as outpatient, rather than inpatient, visits. Removing these two types of patients reduces the potential for skewing mortality rates in either direction.

Private Rooms

Hundreds of studies have been undertaken examining the effects of hospital room design (Ulrich, Zimring, Joseph, & Choudhary, 2004). Architects have studied patient care unit layout and patient room configuration (Ulrich et al., 2004). Both nurses and patients have expressed opinions regarding the effect of room configuration on privacy, confidentiality, and noise (Chaudhury, Mahmood, & Valente, 2006; Hilton, 1985). Patient safety has been studied in relationship to private rooms, including falls, infection, medication errors, other adverse events (Chaudhury et al., 2006; Zoutman et al., 2003).

Decreasing infections, especially nosocomial infections, can increase cost savings (Jarvis, 1996; Plowman et al., 2001). While the general consensus is that private rooms present patient benefits (Stall, 2012a, 2012b, 2012c), there are land, construction, maintenance, and operating costs for the hospital system (Boardman & Forbes, 2011).

Patient Severity Measures

A patient severity measure allows comparisons between patients, between hospital inpatient units, and between hospitals, which recognize that poor outcomes and longer length of stay are more likely for sicker patients. There are many different measures for patient severity. PRISM (Pollack, Ruttimann & Getson, 1988) is commonly used in pediatrics while APACHE is used for adult intensive care patients.

The case-mix index was created by the Centers for Medicare and Medicaid Services (Centers for Medicare and Medicaid Services [CMS], 2012). It is based on diagnostic related group (DRG) codes, and can be used in adult and pediatric patients in any inpatient location. The CMS definition of case mix index is "the average diagnosis-related group (DRG) relative weight for that hospital. It is calculated by summing the DRG weights for all Medicare discharges and dividing by the number of discharges" (CMS, 2012).

Lilford and Pronovost (2010) argued that case-mix index does not account for non-preventable versus preventable deaths and is not a true indicator of quality. On the other hand, in previous studies, Longhurst et al. (2010) used case-mix index. Han et al. (2005) and Del Beccaro, Jeffries, Eisenberg, and Harry (2006) both used the PRISM score, while Al-Dorzi et al. (2011) used the APACHE scoring system. Mekhijan et al.

(2002) used a severity-adjusted length of stay in their study. The data extracted for this study included the case-mix index.

Process Variables

Rapid Response Team Activation

A rapid response team is a nationwide trend that was implemented at University Hospital and the Huntsman Cancer Institute during the study periods. When a nurse believes that a non-ICU patient is unstable, the nurse can call the rapid response team. The team responds within a short period of time and determines whether the patient needs more intensive interventions. Bottle, Jarman, and Aylin (2011) did not include a rapid response team, but that may have been because this is a recent process. Rapid response team activation was included in this study.

Nurse Staffing Hours

One possible confounder for the study outcomes is the number of nursing staff caring for the patients, with increased nurse staffing ratio presumably leading to lower mortality. Furukawa, Raghu, and Shao (2010) calculated nursing hours per patient day (HPPD) by using nurse productive hours divided by patient days. The authors found that registered nurse and nurse aid hours increased during electronic medical record implementation in community hospitals in California but no change in skill mix occurred. They reported conflicting results for length of stay. During CPOE implementation, length of stay, cost, and patient complications increased while mortality decreased. Registered nurse hours were included in this study.

Orders Utilization

Due to the nature of the implementation process at the University of Utah Hospital, there was the opportunity to compare orders placed before and after CPOE implementation. Pharmacy, laboratory, radiology, and medication orders were electronically stored for all implementation phases. In the pre-implementation phase, orders, while written on paper, were entered into the ancillary (laboratory, pharmacy, or radiology) system and therefore ultimately became represented in the data warehouse. In the postimplementation phase, orders placed by providers into the electronic health record were directly recorded in the data warehouse.

Literature Review Summary

Electronic health records, and in particular computerized provider order entry (CPOE) functionality, have been identified as a potential means to support healthcare quality and efficiency, but despite political and economic incentives, implementation has overall been relatively slow. Of the limited literature related to CPOE implementation, most attention has been paid to the changes in mortality. Findings from those studies ranged from improvements, to no change, to worsened outcome.

The design of previous studies varied widely. Prior studies included antecedent and structural factors as potential covariates, but the study designs, populations, and methods were dissimilar. Research on the impact of CPOE implementation continues to be needed due to mixed findings in the literature and because we are still uncertain about the impact of CPOE on patient outcome measures.

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CHAPTER 3

METHODS

Aims

The purpose of this study was to determine the impact of CPOE implementation on mortality rates and length of stay in a large academic setting. The specific aims were:

1. To describe the impact of computerized provider order entry implementation on mortality, controlling for antecedent and structural covariates.
2. To describe the impact of computerized provider order entry implementation on length of stay, controlling for antecedent and structural covariates.

Study Design

This retrospective observational study used a pre-post design. Data were collected at the individual patient level, but the unit of analysis was the patient care unit. Patients were admitted to a patient care unit based on each hospital's criteria, which is typically based on type of illness and bed availability. For some analyses, the patient care units were aggregated by type (e.g., medical-surgical units versus intensive care units).

Sampling

The study took place at an academic health sciences center with three physically separate hospitals. The main hospital at the University of Utah served medical, surgical, intensive care, rehabilitation, and inpatient psychiatric patients for a total of 450 beds.

The second and third facilities served cancer (Huntsman Cancer Hospital) and psychiatric patients (University Neuropsychiatric Institute) and at the time of the study contained 50 and 90 beds, respectively. Pre-CPOE implementation admissions occurred between October 1, 2006 and April 18, 2009, a time frame of 2.5 years. To be included in the pre-implementation sample, patients must have been discharged before April 18, 2009 at 23:59. The CPOE implementation occurred from April 18 to June 1, 2009 and patient visits during the implementation phase were excluded from the analysis. Postimplementation dates contained patients admitted and discharged between June 1st, 2009 and December 31st, 2011, a time frame of 2.5 years.

Eligibility Criteria

Patient Care Units

All patient care units were included with the following exceptions. The study focused on adult patients; therefore, pediatric and newborn intensive care units were excluded. Labor and delivery units were excluded because maternal death rate is formally defined as a death up to 42 days after termination of a pregnancy by any means (World Health Organization [WHO], 2012), and postdischarge data were outside the scope of this project. Units that had not implemented CPOE were excluded from final analyses.

Patient Data

Although the primary unit of analysis was the patient care unit, data from individual patients were aggregated to account for patient antecedent characteristics. Data from patients 18 years and older at the time of admission were included. Patients needed to have a status of “inpatient” and a length of stay of at least 1 day. Patients who were prisoners were not excluded but are not identifiable as prisoners within the data set. Children were excluded because most children go to another facility outside of the University of Utah Hospital and the sample size was not large enough to be meaningful.

Data/Variables

The intervention was the implementation of computerized provider order entry (CPOE) functionality within the electronic health record. CPOE implementation marked an observable change in process at the institutional, patient care unit, and individual patient level. Mortality rates and length of stay were the outcome variables of interest. Deaths were included in the numerator for mortality calculations and each visit comprised an observation in the denominator. Length of stay was computed as the difference between the recorded admission date/time and the recorded discharge date/time, reported as number of days including fractions rounded to 2 decimals (e.g., 1.75 days).

Data were categorized according to the theoretical framework (Coyle & Battles, 1999). Covariates were identified via the literature (used in other CPOE studies) or added because they are known to potentially influence the outcome variables. Demographics, insurance type, and admission via the emergency department were examined to assess the similarity in patient populations in the two groups. Physician resident hours decreased from 100 hours per week to 80 hours per week in 2003, well before the time frame included in this study, so this change was not anticipated to have an impact on this study as it did in Del Beccaro, Jeffries, Eisenberg, and Harry's (2006) study. In addition, computerized clinical decision support was excluded, a priori, from this study. Based on the literature review and the goals of the study, demographics (age at admission, gender, race/ethnicity, area of residence zip code, marital status, smoking status and body mass index), admission via the emergency department, insurance type, private room, patient care unit, palliative care status, rapid response team activation, resuscitation/code activation, and nurse hours per patient care unit were included as potential covariates.

Data Collection

The study was approved by the University of Utah Institutional Review Board. Data came from multiple electronic sources. Clinical data were electronically collected in the organization's clinical data repository. Patient registration data (admit and discharge dates/times, type of admission, patient disposition upon discharge, room type, and patient demographics) were electronically collected in a separate database as were pre-CPOE laboratory, radiology, and pharmacy orders. Nurse staff hours were retrieved from the hospital time-keeping system. Study data were compiled in a data warehouse. Data warehouses aggregate data from disparate systems and link them via a patient's medical record number and the patient's visit/encounter number. Data were stored on a secure server behind the firewall at the University of Utah to ensure the data remained secured, confidential, and intact.

Data Cleaning

As happens with any secondary use of clinical data, the data set required substantial cleaning prior to analysis. The data were collected for clinical care, not research purposes, and it has been well documented that clinical records may contain incorrect or incomplete information (Botsis, Hartvigsen, Chen, & Weng, 2010). At any given time, there are a number of "test" patients in the electronic medical record, which are fabricated records used for training, system testing, and to try to replicate issues that clinicians report. These “test” patients have multiple visits, with upwards of thousands of transactions on their account. These patients, known to the information technology staff, with all of their encounters and data, were removed from the data set. The data were visually and electronically scanned for patterns, such as values that were physiologically unlikely. When difficulties interpreting patterns were found, the committee and the researcher made decisions to repair the data, leave as is, or remove from the analysis.

The data file was examined with descriptive statistics, histograms, and bar charts to determine patterns of missing data and other data quality issues. With the large data set, it was impossible to perform chart abstracts in hopes of replacing incorrect or missing data. However, 10 charts were reviewed in detail, a process that identified logic flaws with the original data extraction query. Electronic health record unavailability due to hardware or software upgrades occurred approximately every 6 months during the study data time frame and was expected to influence the data patterns, but no such pattern was identified during the data quality evaluation.

Analytic Strategy

The goal of this study was to view the CPOE implementation from a system-wide view instead of from a single patient care unit or population. To accomplish this goal, statistical analyses were completed in two phases. The first phase examined demographic variables and potential confounders to ensure the inclusion and exclusion criteria were met and to assess for data quality issues. The purpose of phase 2 was to analyze the main study aims. Traditional Chi square tests of independence and independent *t*-tests were performed, initially. These tests showed great variability within and between patient care units for both length of stay and mortality indices.

However, it was determined that traditional statistical tests were not appropriate to analyze the variables, due to lack of observation independence. Patients could have been in one or more hospital units, during one or more hospital admissions. Consequently, analysis was performed using hierarchical linear models that accounted for repeat visits by the same person, and clustering of patients within patient care units. SAS software (V 9.3) HPMixed procedure was used to assess the continuous dependent variable, length of stay. SPSS software (V 21.0) generalized linear mixed procedure (GLM) was used to evaluate the binary outcome measure, mortality.

Two sets of models were developed. The first set of models analyzed the 22 patient care units as individual, random effects. Analyses showed similarities between patient unit types, so the second set of analyses collapsed the 22 patient care units into major patient unit types: medical/surgical, intensive care, oncology, psychiatry, and rehabilitation.

Figure 3.1 shows the changes in sample size from initial extraction to the analysis subsets. The original data extraction included more than 133,000 observations. Labor and delivery visits and visits in non-CPOE units were excluded (n = 26,695). The second box in Figure 3.1 shows the number of observations per implementation phase.

The “Analyses” section of the diagram shows the number of patients excluded, and the reasons why, for each outcome variable. Visits during the CPOE implementation phase time frame were excluded. This resulted in a length of stay analytic sample equal to 89,818 and 104,153 for the mortality analytic sample.

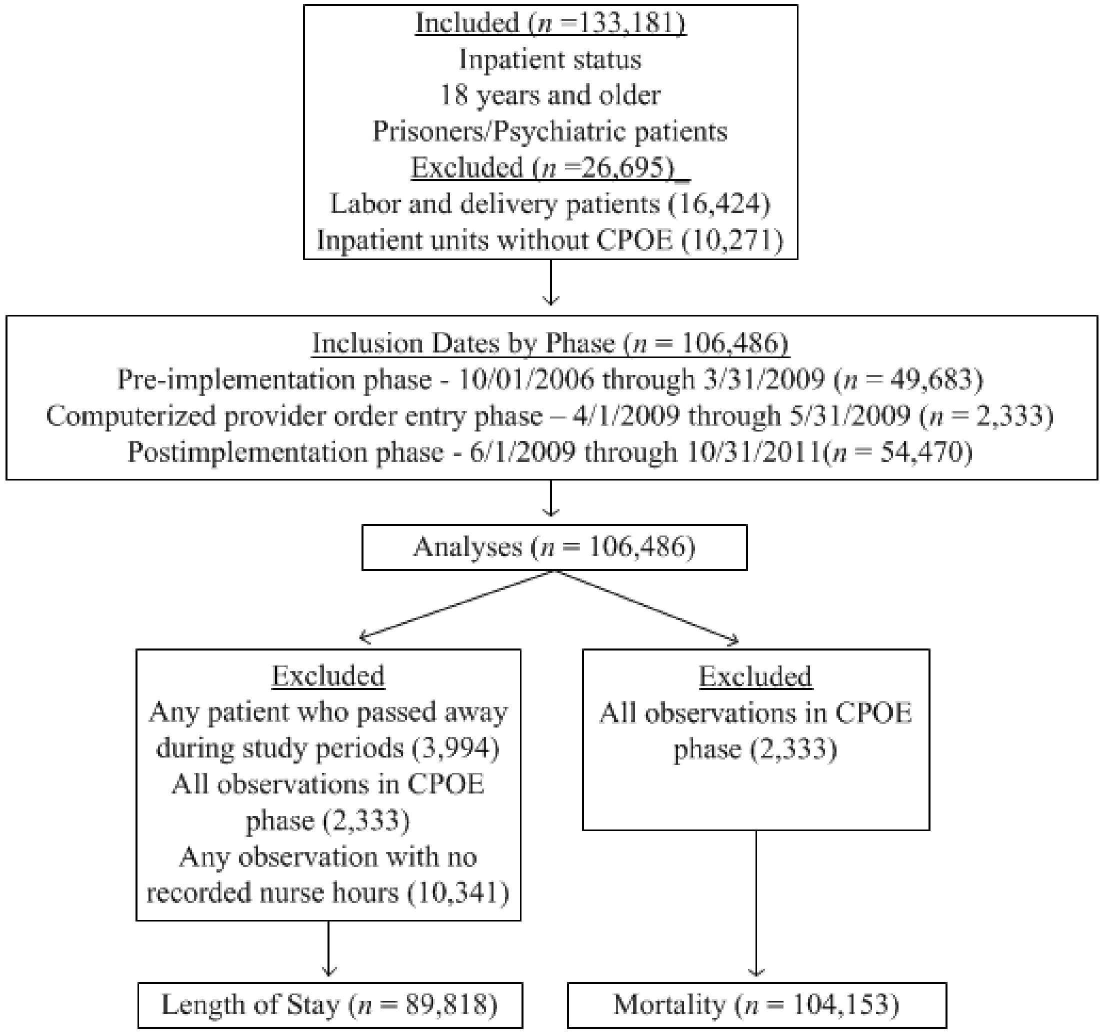

Figure 3.1. Changes in sample size

Alternative Analytic Strategy Considered: Propensity Matching

Propensity matching was considered as a potential analytic approach. Propensity matching attempts to estimate the effect of an intervention by accounting for the covariates that predict receiving the intervention, by means of a derived probability score (Austin, 2011). While this definition sounds like propensity matching would be a reasonable analytic strategy, the method was ultimately rejected for this study.

Unlike nonrandomized studies where propensity matching can be used to reduce selection bias introduced when clinicians decide which intervention a patient will receive (Rosenbaum & Rubin, 1983), all patients in this study received the intervention of CPOE in the postimplementation phase or acted as the control group in the pre-implementation phase. There was no ambiguity of whether or not the patient would receive the intervention. In addition, propensity matching typically uses standard logistic regression (Austin, 2011; Garrido et al., 2014) where an assumption of independence of observations is required. However, patients in this study had the opportunity to have multiple visits; this violates the independence of observation assumptions. Lastly, propensity scores are often used within specific disease processes (Austin, 2011; Garrido et al., 2014). This study did not focus on specific diseases but looked at the system as a whole. Therefore, propensity matching was not used in this study.

Results Presentation Strategy

The results are presented in two articles written for publication. The first article focused on the primary results for study aims. The second article focused on working with large data sets and evaluating data quality. A third results chapter outlines other interesting results, in addition to the findings presented in the two articles.

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CHAPTER 4

THE IMPACT OF COMPUTERIZED PROVIDER ORDER ENTRY (CPOE) ON MORTALITY AND LENGTH OF STAY AT A LARGE ACADEMIC HOSPITAL

The material in this chapter is an article that will be submitted to a high-impact clinical journal. The article presents the major findings from the statistical analyses for length of stay and mortality (the primary study aims). The article is presented here in APA format; citations will be reformatted to match journal submission requirements prior to submission.

Abstract

Background: National reports and legislative changes have spurred the implementation of electronic health records. Mixed results in the literature regarding computerized provider order entry (CPOE) implementation leave open the opportunity and responsibility to further explore the impact on patient outcome measures.

Methods: A retrospective, pre-post design study evaluated the association between CPOE implementation and patient length of stay and mortality while controlling for antecedent, structure, and process variables. Traditional analyses and complex statistical models were used to challenge, with demographic and confounding variables, the impact of CPOE on patient outcomes. The hospital system of interest included a 450-bed general hospital, a 50-bed cancer hospital and a 90-bed psychiatric hospital.

Results: CPOE remained a significant predictor of length of stay and mortality in all statistical models. Length of stay decreased, on average, by 0.90 days. Overall, hospital mortality rate decreased from 1 to 3 deaths per 1000 observations, model dependent, for a potential total decrease of 54 to 162 deaths over the 2.5-year postimplementation period. The decrease in mortality varied by patient care unit.

Conclusions: Challenging the impact of CPOE by controlling for confounders revealed statistically and clinically significant decreases in patient length of stay and mortality at a large academic hospital. These findings suggest the decrease was associated, in part, with CPOE implementation. Mortality rate models were influenced by patient care units and potential confounders, suggesting the need for future studies to account for those influences.

Introduction

Background

The Institute of Medicine (IOM) released two landmark reports, To Err is Human (1999) and Crossing the Quality Chasm (2001), that suggested electronic health records, including advanced functions such as computerize provider order entry (CPOE), could improve healthcare quality and efficiency. The electronic health record is a patient documentation system that contains multiple components such as laboratory and radiology results, nursing and provider documentation, and patient care orders. Computerized provider order entry (CPOE) is a key component of the electronic health record that is expected to influence health outcomes (IOM, 2003).

After the IOM reports, studies began to evaluate the effects of electronic health records, but literature specifically evaluating CPOE implementations has been sparse. Early studies, published in years 2005 to 2009, focused mostly on the pediatric population and showed mixed results with regards to length of stay and mortality outcomes (Amarasingham, Plantinga, Diener-West, Gaskin, & Powe, 2009; Del Beccaro, Jeffries, Eisenberg, & Harry, 2006; Han et al., 2005; Keene et al., 2007). The 2009 American Recovery and Reinvestment Act (ARRA) legislation contained *Meaningful Use* requirements, offering financial incentives to hospitals and providers who installed and used certified electronic health records in a timely fashion, and financial penalties to those who failed to do so (U.S. Government, 2009). These initiatives resulted in hospitals spending millions of dollars, and large amounts of time, installing or revising electronic health record technology (IOM, 2012). After the ARRA legislation was enacted, three more articles were published discussing the effect of CPOE on patient outcome measures

(Al-Dorzi et al., 2011; Longhurst et al., 2010; Miller & Tucker, 2011), also showing mixed results.

The previous studies used a variety of implementation strategies, and evaluations occurred over varying time periods, making it difficult to compare the findings directly. With almost all other EHR components implemented and an isolated computerized provider order entry implementation at our institution, a unique and relatively uncommon occurrence, we had the opportunity and the responsibility to assess the impact of CPOE implementation on nationally referenced outcome measures.

Implementation Chronology

This study was conducted at an academic medical center containing a 450-bed medical and surgical hospital with an acute psychiatric care ward, a 50-bed cancer hospital, and a 90-bed psychiatric hospital. Figure 4.1 shows the progression of electronic health record implementation, which occurred in phases over several years. The initial phase (1A) began in 1999 and included electronically laboratory and radiology results. Paper-based medication orders were transcribed by pharmacists into an electronic pharmacy system. The next phase, which was called pre-CPOE phase for this study (1B) commenced in 2007 and included electronic nursing documentation and medication administration record (EMAR); orders remained paper-based. Semistructured electronic provider notes were implemented department-by-department starting in 2008 (1B). The phased, lengthy implementation of the electronic health record components resulted in an isolation of the computerized provider order entry functionality, which was implemented for all types of orders in 2009. This provided the opportunity to examine the impact of CPOE during the postimplementation phase (1C) separate from other EHR functionality.

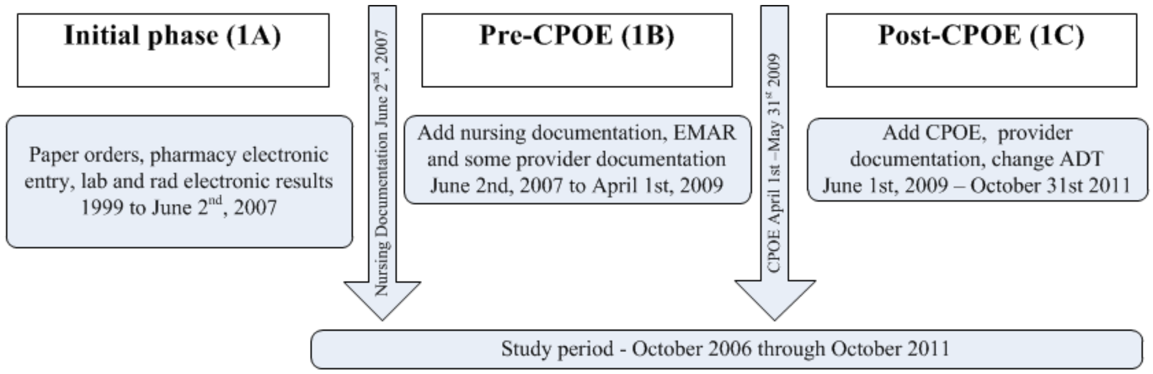

Figure 4.1 Electronic health record implementation timeline at the University of Utah

Methods

Design

This retrospective, pre-post design study was intended to explore the impact of CPOE on length of stay and mortality, two nationally referenced outcome indicators that are common benchmarks for hospitals. Confounders cited in the literature as potential influences on mortality or length of stay were included, to provide a robust estimate of the impact of CPOE implementation. The specific aims were:

1. To describe the impact of computerized provider order entry implementation on length of stay, controlling for antecedent and structural covariates.
2. To describe the impact of computerized provider order entry implementation on mortality rates, controlling for antecedent and structural covariates.

Theoretical Framework

Donabedian's Structure, Process, Outcome conceptual model (Coyle & Battles, 1999; Donabedian, 1966) guided the study (Figure 4.2). *Antecedent* variables represented patient demographics (age, gender, race, ethnicity, marital status), and potential confounders that may vary with each patient visit: smoking status, area of home

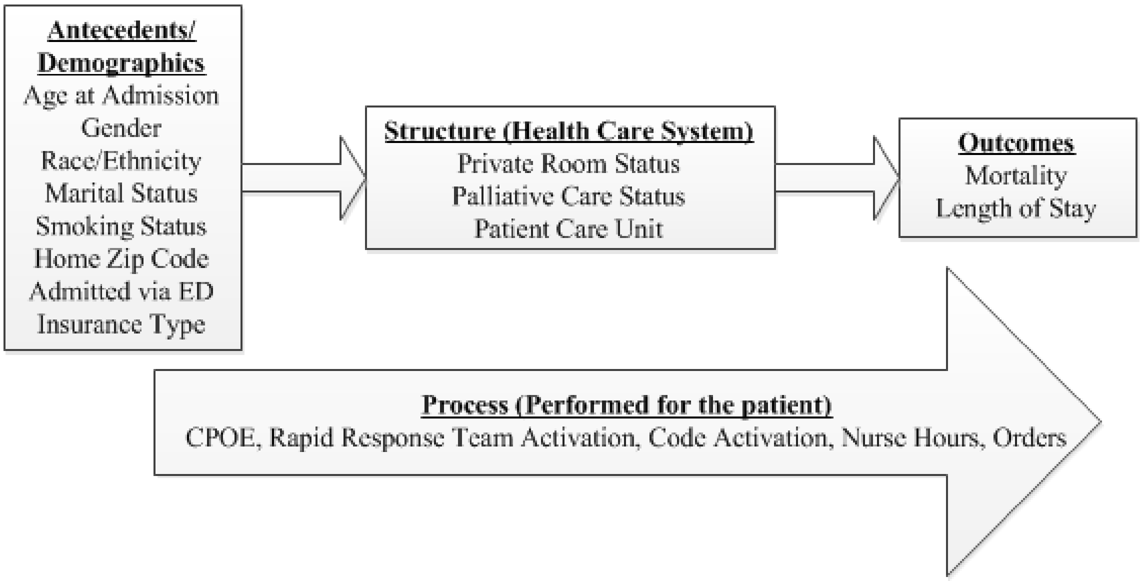

Figure 4.2 – Study variables

residence, admission via the emergency department, and insurance type.

S*tructure* variables reflect the healthcare setting: private versus semiprivate room, patient palliative care status, and patient care unit. *Process* variables reflect actions and patient care activities: CPOE implementation (the independent variable), rapid response team activation, resuscitation team activation, registered nurse hours, and orders utilization.

Sampling

This study was approved by the University of Utah Institutional Review Board. Data were extracted from the clinical data warehouse and from administrative databases. Hospital visits by patients 18 years and older, admitted for longer than one day with a status of *inpatient*, were included in the study (*n* =133,181). Pediatric patient visits were excluded because most pediatric patients are admitted to the nearby children's hospital, thus making the sample of children too small to be meaningful. Labor and delivery visits were excluded from the study because mortality rate for labor and delivery patients (*n* =26,695) is defined differently from mortality for other hospital patients (World Health Organization [WHO], 2012.). Prisoners and psychiatric patients were not identified as such, and were not excluded from the analysis. Patient visits were categorized as being in the pre-CPOE phase if the visit admission date was between 10/01/2006 and 3/31/2009 (*n* = 49,683). The post-CPOE phase included patients admitted between 6/1/2009 and 10/31/2011 (*n* =54,470). Both phases were 2.5 years in length. Patients admitted during the CPOE implementation process (4/1/2009 through 5/31/2009) were excluded from the analyses (*n* =2,333).

Figure 4.3 shows the inclusion and exclusion criteria along with the progression of sample sizes. The unit of observation was the hospital visit. Patient visits initially classified as a short-stay or same-day surgery were included only if the visit status was changed to inpatient and the patient length of stay was greater than 24 hours. Patient visits that encompassed the CPOE implementation time frame were excluded. The mortality sample included 104,153 observations. The length of stay sample excluded patients who died, and visits that were missing nursing hours data. The LOS sample included 89,818 observations.

Statistical Analysis Strategy

The goal of this study was to examine the CPOE implementation from a system-wide view. Statistical analyses were performed by the first author under the supervision of Drs. Donaldson, Pett, and Sward. Preliminary evaluations examined all variables to ensure inclusion and exclusion criteria were met. Individual variables were examined in isolation using traditional statistical analyses for the preliminary analyses.

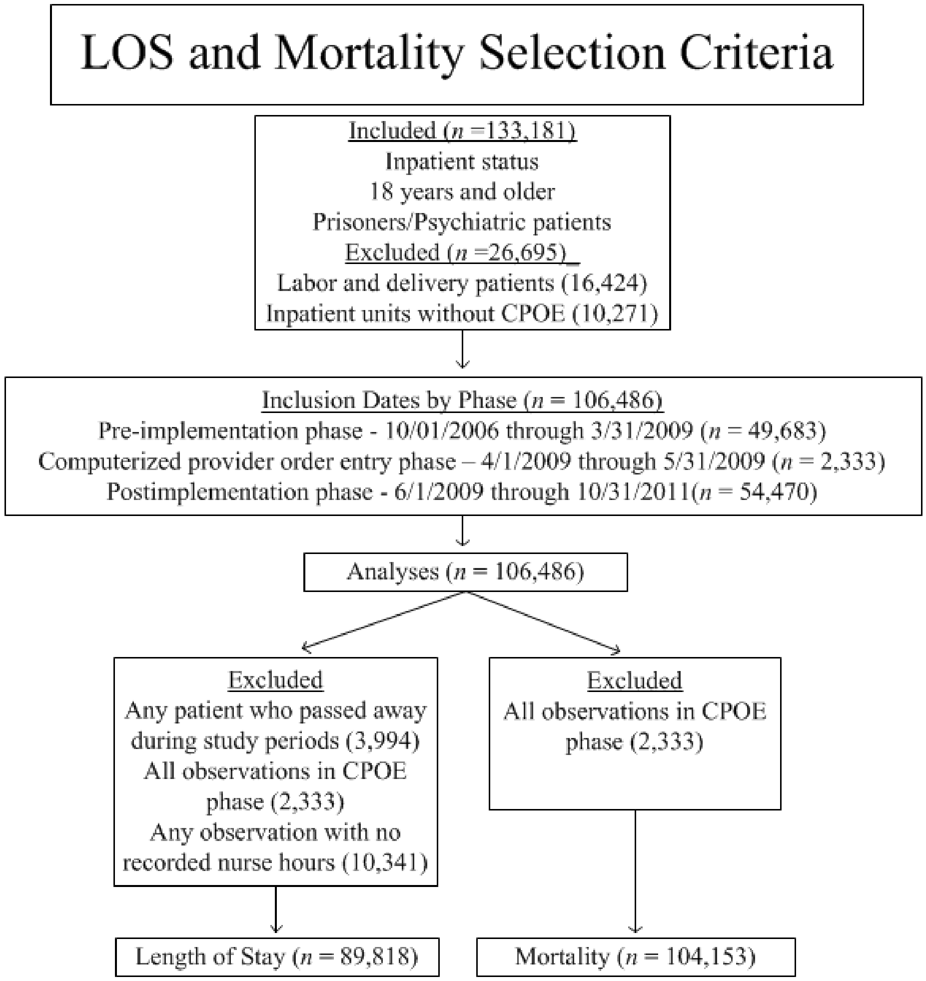

Figure 4.3 – Selection criteria for length of stay and mortality subsamples

Although the unit of observation was the patient visit, the unit of analysis was the patient care unit. Traditional statistical approaches, such as chi square and *t*-tests, were not appropriate for the final analysis, in part due to the clustering (nesting) of observations caused by multiple visits or a visit that spanned multiple patient care units. This clustering violates the assumptions about independence of observations. In addition, several variables were not normally distributed. Therefore, Hierarchical Linear Modeling approaches were chosen that could account for clustering and non-normal distributions. Length of stay (a continuous-level outcome variable) was assessed with the HPMixed procedure in SAS version 9.3. Mortality, a categorical outcome variable, was assessed with Generalized Linear Mixed (GLM) procedures in SPSS software version 21.0. All covariates were entered into the hierarchical model and removed in a backward step-wise fashion until only the statistically significant variables remained in the model.

Results

Sample Characteristics

The initial data extraction, including the CPOE observations, consisted of 106,486 hospital inpatient visits: 49,683 in the pre-CPOE phase, 2,333 during CPOE implementation, and 54,470 in the post-CPOE phase. Of these, 62.2% of the patients had only one visit while 18.3% of the patients had 2 visits. The remaining 20% of the patients had between 3 and 46 visits during the study period. Due to excessive missing values, body mass index (60% missing) and the patient severity indicator, case mix index, (25% missing) were excluded from final analyses.

Table 4.1 outlines the demographic characteristics for the 104,153 patient visits in the pre- and postimplementation phases. Males (50.8%) and females (49.2%) were evenly divided and the majority of patients identified their race and ethnicity as Caucasian (76.4%) and not Hispanic (69.9%). Most were married (53.4%) and 26.3% were single. Although the organization is a referral hospital for a five-state area, more than three-quarters (77%) of the sample listed Utah as their area of home residence. The majority of patient visits (85.8%) neither showed the patient admitting to using tobacco products nor had nurse documentation for smoking cessation materials; these patient visits were categorized as *nonsmoking patient* for analyses. Patients were admitted to the hospital directly from the emergency room (possibly indicating more severe illness) for 31.6% of

Table 4.1. Sample characteristics by implementation phase

Covariates	Pre *n* (%)	Post *n* (%)	Total *n* (%)
Gender			
- Females	25098 (50.56)	26106 (47.93)	51204 (49.16)
- Males	24584 (49.53)	28364 (52.07)	52948 (50.84)
Race			
- White/Caucasian	36753 (74.04)	42848 (78.66)	79601 (76.43)
- People of Color	2190 (4.41)	2871 (5.27)	5061 (4.86)
- Not reported	10740 (21.64)	8751 (16.07)	19491 (18.71)
Ethnicity			
- Hispanic/Latino	3143 (6.33)	3469 (6.37)	6612 (6.35)
- Not Hispanic/Not Latino	30889 (62.23)	41974 (77.06)	72863 (69.96)
- Not Reported	15651 (31.53)	9027 (16.57)	24678 (23.69)
Marital Status			
- Married/Partnered	26732 (53.85)	28858 (52.98)	55590 (53.37)
- Single	12742 (25.67)	14644 (26.88)	27386 (26.29)
- Widowed	4090 (8.24)	3948 (7.25)	8038 (7.72)
- Divorced/Separated	5456 (10.99)	6194 (11.37)	11650 (11.19)
- Not Reported	663 (1.34)	826 (1.52)	1489 (1.43)
Home zip code			
- UT	38145 (76.85)	42102 (77.29)	80247 (77.05)
- MT, ID, NV, WY	7907 (15.93)	9401 (17.26)	17308 (16.62)
- Other location	3631 (7.31)	2967 (5.45)	6598 (6.33)
Smoking patient			
- Yes	3838 (7.73)	10786 (19.8)	14624 (14.04)
- No	45845 (92.36)	43684 (80.2)	89529 (85.96)
Admitted via ED			
- Yes	15367 (30.96)	17505 (32.14)	32872 (31.56)
- No	34316 (69.13)	36965 (67.86)	71281 (68.434)
Insurance Type			
- Private	24762 (49.89)	24548 (45.07)	49310 (47.34)
- Government	379 (0.76)	1017 (1.87)	1396 (1.34)
- Medicaid	4659 (9.39)	5430 (9.97)	10089 (9.69)
- Medicare	16420 (33.08)	19233 (35.31)	35653 (34.23)
- Self-pay	2995 (6.034)	3858 (7.08)	6853 (6.58)
- Other	468 (0.94)	384 (0.7)	852 (0.82)

Table 4.1 continued

Covariate	Pre *n* (%)	Post *n* (%)	Total *n* (%)
Room Status			
- Private room	14074 (28.35)	37425 (68.71)	51499 (49.45)
- Semi-private room	23778 (47.9)	5166 (9.48)	28944 (27.79)
- Not reported	11831 (23.83)	11879 (21.81)	23710 (22.76)
Palliative Care Status			
- Yes	838 (1.69)	2137 (3.92)	2975 (2.86)
- No	48845 (98.4)	52333 (96.08)	101178 (97.14)
Rapid Response team activated			
- Yes	190 (0.38)	468 (0.86)	658 (0.63)
- No	49493 (99.71)	54002 (99.14)	103495 (99.37)
Code/resuscitation activated			
- Yes	124 (0.25)	228 (0.42)	352 (0.34)
- No	49559 (99.84)	54242 (99.58)	103801 (99.66)
Age			
- Mean, median, mode	50.75, 51, 55	52.27, 53, 57	51.54, 52, 57
Sample size	49683	54470	104153

Totals may not equal 100% due to rounding errors the patient visits. Almost half of the patients (47.3%) had documentation of private insurance for their hospital visit, while 34.2% had Medicare and 9.7% had Medicaid insurance.

Nearly half (49.5%) of the patients stayed in a private room and 27.2% in a semi-private room during their inpatient visit. Room status for the remaining 22.8% of visits was unknowable due to room configuration and a change in the patient tracking and financial system during the course of the study. Only 2.9% of the patients had documentation of palliative care status for the visit. Even fewer visits included rapid response team activation (0.6%) or cardiac/respiratory resuscitation team activation (0.3%). Patient age was consolidated to ranges for final analyses, but in the overall sample, the mean, median, and mode for age were 51.54, 52, and 57 years, respectively. The mean, median, and modal age appeared slightly lower in the pre- (50.75, 51, 55) versus post- (52.27, 53, 57) phase.

Statistical differences were noted between the pre and post phases, as shown in Table 4.2. The post-CPOE phase contained 5,200 more hospital visits and 4.14% more males than females. Age was categorized in 10-year increments. The pre-CPOE phase had 3.4% more patients between the ages of 18-29 at the time of their visit, while the post-CPOE phase had 4% more visits by patients between the ages of 50 and 69. There were 1.21% more patients who reported marital status as single in the post-CPOE phase. More patients identified their race and ethnicity as White/Caucasian (4.6%) and not Hispanic (14.83%) in the post-CPOE phase; however, the pre-CPOE phase contained more undocumented values for race (5.57%) and ethnicity (14.96%).

Table 4.2 Differences in covariates between pre and post phases

Covariate	Chi-Square (d.f.), *p* value	Cramer's V
Gender	69.63 (1), $p < .0001$	0.03
Age (categorized)	329.81 (4), $p < .0001$	0.06
Marital status	60.62 (4), $p < .0001$	0.02
Race	825.20 (2), $p <.0001$	0.09
Ethnicity	3267.37 (2), $p <.0001$	0.18
State of home residence	165.29 (2), $p <.0001$	0.04
Smoking patient	2862.00 (1), $p <.0001$	0.17
Admitted via ED	17.46 (1), $p < .0001$	0.01
Insurance type	453.37 (4), $p < .0001$	0.07
Room status	22383 (2), $p <.0001$	0.46
Palliative care status	467.61 (1), $p <.0001$	0.07
Rapid response team activated	93.32 (1), $p < .0001$	0.03
Code/resuscitation activated	21.53 (1), $p < .0001$	0.01

The increased documentation of race/ethnicity was likely due to the change in financial system during the postimplementation phase, which prompted registration staff to ask patient this question. The pre-CPOE phase contained fewer visits in which patients reported home residence in Utah (0.5%). More patient visits (12.1%) in the post-CPOE phase documented the patient was a smoker or received smoking cessation material (implying that the patient was a smoker). This increase may have been due to a change in nursing documentation policy, in which smoking status became a required field.

More patients, 1.2%, were admitted to the hospital from the Emergency Department in the post-CPOE phase. In addition, more patients in the pre-CPOE phase, 3.82%, claimed a private-pay insurance type for the visit, whereas 2.23% more patients in the post-CPOE phase reported Medicare insurance for the visit. During the post-CPOE implementation phase, 40.4% more patient visits were assigned a private room. There was an increase in documentation of palliative care status (2.2%), rapid response team activation (.5%), and code activation (.2%) in the post-CPOE phase.

Chi-square of independence tests were performed to determine differences between the pre and post phases. Statistical differences between the pre and post phases were found for most covariates. Given the large sample size, finding statistically significant differences was not unexpected; large samples can show statistical significance for even trivial differences (Lanztz, 2013). Therefore, effect sizes were also calculated. Table 4.2 includes the Cramer's V, which indicates strength of association for Chi-square tests (Pett, 1997). Most covariates showed only a weak association. Room status was the only covariate to show a moderate association between the pre- and post-implementation phases. The differences in room status between the pre and post phases are likely due to the addition and privatization of hospital beds during the postimplementation phase.

Impact of CPOE implementation

Preliminary analyses suggested that CPOE was significantly associated with length of stay. All covariates were initially included in the hierarchical models. Backward step-wise analysis was performed. All nonsignificant variables were progressively removed from the models until the model only contained the variables that were statistically associated with length of stay, when examined as a set. Two sets of models were developed for each of the dependent variables. The first evaluated each of the 22 patient care units as the unit of analysis. The second set of models aggregated the patient care units into 5 major unit types: medical/surgical, intensive care, oncology, psychiatry, and rehabilitation. Patient care units (or unit type) and individual patients were listed as random effects for length of stay analyses. Only the patient care unit was evaluated as a random effect for the mortality analyses. The individual patient was evaluated as a fixed effect because the patient did not have a unique, unchanging risk of dying.

Length of Stay

The variable "length of stay" was not normally distributed and was therefore transformed to a more normally distributed data set using a Box-Cox nonlinear formula (Box & Cox, 1964). All significance tests were run using the transformed data. Because of the nonlinear transformation, results are nonadditive and cannot be directly interpreted (Box & Cox, 1964; Singer & Willet, 2003). To assist with interpretation, results were back-transformed using the inverse Box-Cox formula.

Table 4.3 shows results from the final statistical analyses. Covariates remaining in the models as significant influences on length of stay were the following: age, race, marital status, zip code, insurance type, private room status, smoking status, admitted via ED, palliative care status, code activated, rapid response team activated, and nurse hours. Ethnicity was associated with LOS in the model assessing units independently, but not in the model that aggregated units by type.

Controlling for potential confounding variables, the impact on length of stay associated with CPOE remained significant, with a decrease in overall hospital length of stay of 0.90 (Table 4.3A) and 0.92 (Table 4.3B) for the 2 models. In the model representing five patient care unit types (Table 4.3B), the confidence interval was wider, reflecting the differential effect of the individual patient care unit. Nevertheless, there were clinically and statistically significant decreases in length of stay in both models.

Table 4.3. Length of stay and mortality statistical results

Sample	*n*	Pre-estimate	Pre-CI	Post-estimate	Post-CI	Decrease days/deaths	*F*	df (num,den)	*p*
				Length of Stay					
22 units (A)	89818	5.18	3.96, 6.99	4.26	3.32, 5.61	0.90	721.33	1, 89786	< .0001
5 groups (B)	89818	5.70	3.32,11.40	4.88	2.92, 9.31	0.92	451.03	1, 89788	< .0001
				Mortality					
22 units (C)	104153	0.008	0.002, 0.027	0.005	0.002, 0.018	3	38.01	1, 104130	0.001
5 groups (D)	104152	0.006	0.002, 0.095	0.005	0.002, 0.081	1	6.60	1, 104125	0.010

Mortality

Even though gender and area of residence were predictors of mortality when examined independently, they did not remain significant when considered in the hierarchical linear models. In the model using individual patient care units, race, smoking status, and nurse hours were also not statistically significant and removed from the final model. Covariates remaining in the models as predictors of mortality in both models were the following: age, marital status, insurance type, private room status, and admitted via ED. Ethnicity (and not race) was a significant predictor of mortality in the model evaluating units independently, whereas race (and not ethnicity) was a mortality predictor in the model that grouped units by type. The model that grouped units by type also included smoking status and nurse hours as predictors of mortality.

To test a potential conflict of explanatory covariates acting as intermediate outcomes (mediators or moderators), palliative care status, code activation, and rapid response team activation were evaluated. Because inclusion of these variables in the models unduly emphasized the impact of CPOE on mortality (the apparent decrease in mortality was unrealistically large), they were removed from final models. Palliative care status has been controversial, in mortality rate computations; with some arguing that patients in palliative care should, by definition, be eliminated from mortality rate computations (Cassel, Jones, Meier, Smith, Spragens, & Weissman, 2010). Two processes have logical associations with mortality and are generally thought to be independent of care processes such as CPOE: code activation and rapid response team activation. It is plausible that these variables might represent individual decisions, rather than the impact of a system-wide process such as CPOE.

The 2 final models showed decreases in mortality (Table 4.3), associated with CPOE implementation after accounting for potential confounders. The first model, containing the 22 patient care units (Table 4.3C), showed mortality decreased by 3 deaths per 1000 observations or 162 deaths over the course of the study. The model aggregating patient care units by type (Table 4.3D) showed a decrease of 1 death per 1000 visits, resulting in a decrease of 54 deaths over the 2.5 year postimplementation phase. The models revealed a unit impact where some patient care units had an increase in deaths while other units had a decrease or no change in deaths.

Discussion

Main Findings

Length of Stay

This study showed, on average, a decrease in length of stay of almost 1 day per hospital visit. Potential benefits for discharging patients 1 day early include the ability to reduce exposure to nosocomial infections, reduced risk of receiving an incorrect medication, reduced financial burden to patients and insurance companies, and increased hospital bed availability. The impact of CPOE on length of stay likely reflects an increase in efficiency when placing patient orders, with subsequent reduction in time receiving laboratory and imaging results and initiating care. Decreasing the processing time has the potential to decrease the length of stay. For example, it is plausible that pain was more effectively managed because pain medications were ordered and administered more efficiently in the post-CPOE phase. Better pain management could lead to faster time to ambulation and consequently meeting other discharge criteria more quickly. Previous studies reported a decrease in turn-around time for lab order entry and results (Mekhijan, Saltz, Rogers, & Kamal, 2003). Faster medication administration has been documented after electronically placing medication orders (Jensen, 2006).

It is possible that the decrease found in this study may represent a natural progression of length of stay. Hospital length of stay has decreased over the last 50 years (Organisation for economic co-operation and development [OECD], 2009). Most research literature related to length of stay focuses on specific disease states. Potential explanations for the overall long-term reduction in length of stay include better diagnostic skills, an increase in knowledge, change in insurance billing policies, more minimally invasive procedures, and more appropriate use of home health, rehabilitation, and skilled nursing facilities.

Even though length of stay has decreased over the past 50 years, and can be impacted by multiple factors, it is reasonable to believe computerized provider order entry implementation had an impact on length of stay in this academic medical center. All models in this study showed a clinically and statistically significant decrease in length of stay during the postimplementation phase even when controlling for the many covariates.

Mortality

Like previous studies, this study showed mixed results for the impact of CPOE on mortality. Overall, there was a statistically and clinically significant decrease in mortality rates for the 2 statistical models. When evaluating CPOE implementation by individual patient care units (Table 4.2C), the model showed a larger decrease in mortality than when the units were aggregated by type (Table 4.2D). However, wide variations were found when observing the mortality at the patient care unit level. Most medical/surgical patient care units showed a decreased mortality rate, while the intensive care units increased. Psychiatric units had only one death for the entire study. This suggests the choice of patient care units in a study could profoundly influence the study findings. The choice of patient care units may, in part, explain some of the mixed findings in previous literature evaluating CPOE and mortality.

Mortality is a complex phenomenon; many factors can contribute to this outcome. Mortality rate as an outcome measure appears to respond strongly to the presence of certain covariates. One structure variable, palliative care status, and 2 process variables, code team activation, and rapid response team activation, unrealistically magnified (tripling or quadrupling) the mortality decrease. Consequently, these covariates were removed from the final models. Others investigators have suggested that mortality may not be an appropriate outcome measure with regards to CPOE implementation (Ammenwerth et al., 2006).

Limitations and Strengths

The data for this study were from a single academic medical center; other institutions may have different results. The study purposefully included a large sample size; but because of that, even small changes in the outcome measures may be statistically significant. Neither 30-day readmissions, nor deaths occurring within 30 days of discharge, were evaluated. With regards to length of stay, this study did not account for insurances policy changes. Other changes in healthcare were also not considered, including the increase in the number of minimally invasive procedures and outpatient surgeries, or the longitudinal changes in referrals to home health services, skilled nursing facilities, and rehabilitation units. These items may be evaluated in future studies by including 30-day hospital readmissions and 30-day, postdischarge mortality rates. Future studies could further examine the unit effect by including patient severity indicator and additional patient demographics.

This study was unique in examining the impact of CPOE from the perspective of the entire hospital system, which included multiple hospitals. Most previous studies focused on a single patient care unit or a subset of patient care units. The study was also unique in the breadth of potential confounders that were used to challenge the impact of CPOE on length of stay and mortality rate. The robust statistical modelling technique, which accounted for clustering, multiple patient visits, and non-normal distributions, was also a strength of this study.

Conclusions

After accounting for confounders, there remained a beneficial clinical association with both length of stay and mortality after CPOE implementation. Length of stay decreased, on average, 0.90 days per visit. Mortality rate, depending on the model, decreased by 1 to 3 deaths per 1000 patient visits for a potential total decrease of 54 to 162 deaths over 2.5 years, after CPOE implementation. Despite the robust nature of the statistical methods employed in this study, mortality appeared to be overly sensitive to certain structure (palliative care status) and process (code and rapid response team activation) variables in this study. Mortality results also varied widely between patient care units. Future studies need to be performed at other institutions, academic and community alike, to validate these findings.

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CHAPTER 5

WORKING WITH LARGE HEALTHCARE DATABASES: A CASE STUDY

The material in this chapter is an article that will be submitted to *Nursing Research* or to a similar high-impact clinical research journal. The article presents the data cleaning and preparation phase of the study. The article is presented here in APA format; citations will be reformatted to match journal submission requirements prior to submission.

Abstract

Background: With the transition toward electronic health records, large data sets are becoming more accessible for nursing research. Secondary analyses are useful and necessary but have inherent problems. The data were collected for clinical purposes, rather than specific research questions; errors, missing data, and other issues can introduce potential bias into research analyses.

Objectives: The objectives of this article are to introduce nurse researchers and nursing students to secondary analysis of EHR data and data quality evaluation, and to describe a pragmatic process for data management. This case study uses real-life examples to illustrate issues that can arise during secondary analyses.

Method: A retrospective pre-post design secondary data analysis of inpatient visits in a large academic medical center was conducted to determine the impact of computerized provider order entry on mortality and length of stay. Extensive data quality evaluations were performed prior to the main research analyses.

Results: Pragmatic processes to facilitate data acquisition are described, including pre-research evaluations and communication tips to support accurate data requests. Methodical, step-by-step processes to evaluate data quality are described, with examples from the case study illustrating data quality issues. Just as in primary data collections, it is critical to evaluate compliance with inclusion/exclusion criteria. The outcome variables were examined to determine if the overall research question could be answered. Data quality for demographic variables and potential covariates was examined next. Variables were examined along the dimensions of completeness, correctness, concordance, plausibility, and currency to determine each variable's fitness for use in answering the

questions of this research study. Some data quality issues could be addressed and corrected, other issues led to a decision to omit certain variables from the analyses. These evaluations and decisions contributed to confidence that the final, overall data set was fit for use for the research analyses. Finally, tips and tricks for meticulous data management that will maintain a high-quality data set are presented.

Discussion: Secondary data analysis will continue to expand as more healthcare entities implement electronic health records. Meticulous data management processes and data quality evaluations can determine the extent to which a data set is *fit for use* to answer research questions, contributing to valid and reliable results of the secondary data analyses. This case study contributes to the body of knowledge by describing a process to expedite large, secondary analyses, using real-life examples. More case studies are needed to refine the processes and contribute to the lessons learned if nurse researchers intend to become facile at secondary data analysis.

Background

In 2013, basic electronic health records (EHR) were implemented in 59% of general acute care hospitals (Charles, Gabriel, & Furukawa, 2014), a more than three-fold increase since 2010 (DesRoches et al., 2013). The increase in EHR usage has provided an opportunity to use data collected at the bedside for research purposes, an emerging form of secondary data analysis (Safran et al., 2007), and offers nurse researchers an opportunity to use data collected by a variety of disciplines to answer unique nursing practice and research questions (Magee, Lee, Giuliano, & Munro, 2006). Funding agencies such as the National Institutes of Health encourage secondary data analysis, especially use of EHR data to support clinical research (Botsis, Hartvigsen, Chen, &

Weng, 2010; Weiskopf & Weng, 2013). Additionally, analysis of EHR data is important in evaluating healthcare systems and system-wide interventions (Botsis et al., 2010; Safran et al., 2007) by providing a window into healthcare processes and outcomes that is representative of actual patients and the real-life environment (Weiskopf & Weng, 2013).

Electronic health records are primarily intended to document clinical care and drive financial reimbursement. The data from these systems have also been used for safety monitoring and quality assurance, accreditation, marketing, and other business purposes. Recently, EHR data have played an increasingly critical role in generating knowledge for evidence-based practice and formal research (Horn, Gasaway, Pentz, & James, 2010; Safran et al., 2007; Smith et al., 2011). However, because the data were collected for other purposes, there is the concern that clinical data may not be fit for use in research. To address the fit-for-use conundrum, Weiskopf and Weng (2013) developed a theoretical framework to guide novice big-data researchers. This article fills the void between theory and practical application by introducing a pragmatic process to assist researchers with making their secondary data fit for research use.

EHR and Secondary Analysis

The increasing use of EHR data for research is inevitable because the data can reflect economic components, care quality, and efficiency (Murdoch & Detsky, 2013). Secondary analysis is the use of data collected for a different purpose (Smith et al., 2011) and is an increasingly common research method (Polit & Beck, 2012). It has long been recognized that secondary analysis of existing data offers advantages for nursing research, particularly in terms of feasibility, timeliness, and cost-effectiveness for data collection (Jacobson, Hamilton, & Galloway, 1993; McArt & McDougal, 2007). Benefits of using secondary data include shortened data collection time (Magee et al., 2006), reduced expense, and potential increased generalizability (Coyer & Gallo, 2005; Magee et al., 2006). Other reported benefits for researchers include the opportunity to demonstrate expertise and productivity, the ability to inform primary research, and as a source of information for grant generation (Smith et al., 2011).

There are issues and challenges associated with using secondary data for research purposes, including issues specific to electronic health records. Electronic health record data have been well documented as having data quality issues (Botsis, Hartvigsen, Chen and Weng, 2010; Goodwin, VanDyne, Lin, & Talbert, 2003; Kahn, Raebel, Glanz, Riedlinger, & Steiner, 2012; Palma, 2013). Electronic health record data are collected for clinical purposes; certain data may have not been seen as clinically relevant during the patient's visit and therefore were not documented. The data may be stored in a different portion of the EHR than expected (Botsis et al., 2010), or may not have been collected using standardized approaches (Kahn et al., 2012).

Healthcare data are complex systems (Smith et al., 2011), with high data volume, and heterogeneous data (mixed data types and formats). These characteristics are more pronounced when the health data are electronically distributed amongst multiple databases and specialty systems (Safran et al., 2007; Smith et al., 2011). Selecting the appropriate data source(s) and understanding how variables were operationalized and measured is the first step in working with a large data set. The next steps involve evaluating data quality and preparing the data for analysis. Using these steps will help ensure the data is fit for use in research studies.

Conceptual Framework

One of the most broadly adopted conceptualizations is that data quality is defined by *fitness for use*, that is, the appropriateness of the data for a particular purpose (Juran, 1974; Kahn, Raebel, Glanz, Riedlinger, & Steiner 2012; Weiskopf & Weng, 2013). Juran (1974) explained *fitness for use* for everything from manufacturing to farming and how these products or services have a purpose. If the product meets the needs of the "user", not the manufacturer, then the product is said to be fit for use. The purpose of data is to generate new knowledge. If the data do not generate new knowledge, then the data cannot be fit for use. Furthermore, a data set may be fit for use to answer one research question, but not fit for use for another study. Kahn and colleagues (Kahn, Raebel, Glanz, Riedlinger, & Steiner, 2012) expanded on Juran's *fitness for use* concept, by describing a process to analyze data quality.

Weiskopf and Weng (2013) designed a conceptual framework that identifies five dimensions of data quality. A group of investigators known as the Data Quality Collaborative is currently building on that work to validate a comprehensive list of data quality dimensions (Data Quality Collaborative, 2013), but the results of their work are not yet available. Weiskopf and Weng's (2013) five dimensions, combined with processes described by Kahn et al. (2012), were used to identify data quality issues during a year-long data analysis phase. The five dimensions are: *completeness*, *correctness*, *concordance*, *plausibility* and *currency*.

- *Completeness* - This is the most commonly reported dimension of data quality; it is primarily a reflection of the amount of present/missing data in the electronic record (Weiskopf & Weng, 2013).

- *Correctness* – Defined as the truth of the data (Weiskopf & Weng, 2013). Kahn et al. (2012) defined correctness using 2 descriptors: accuracy (free of error) and objectivity (unbiased and impartial).
- *Concordance* - Is concerned with agreement. The data must represent the research questions as well as the agreement between data elements (e.g., pregnancy tests should not be reported on male patients) and data sources (e.g., ethnicity in the financial system and the clinical system) (Kahn et al., 2012; Weiskopf & Weng, 2013).
- *Plausibility* – Synonyms include believability, trustworthiness, accuracy, and validity (Kahn et al., 2012; Weiskopf & Weng, 2013). An example of data that lack plausibility is the when patients have a documented BMI of zero.
- *Currency* - Currency refers to the extent to which the research data set represents data from the desired time period (Weiskopf & Weng, 2013). Kahn (2012) labels this "timeliness" and adds the need for a sufficient number of measures over time to detect a clinical state. More broadly, currency can refer to all aspects of time, which is crucial in an EHR containing longitudinal data.

Need for Case Studies

Even with concerns related to data quality, the rapid increase in electronic health record usage is driving translational science, including practice-based evidence (Horn et al., 2010; Murdoch & Detsky, 2013) and nursing research toward secondary analysis of EHR data (Murdoch & Detsky, 2013). Unfortunately, there is no standard data element set that is used across all EHR systems (Botsis, Hartvigsen, Chen, & Weng, 2010) and there is no standard method for assessing or reporting data quality (Weiskopf & Weng, 2013). Because there is as yet no consensus regarding EHR data quality, effective strategies for secondary use of EHR data will need to be accumulated from case studies shared with the research community (Botsis et al., 2010; Weiskopf & Weng, 2013).

Objective

This article is written for nurse researchers who are new to using large data sets and who intend to obtain research data from an electronic health record. Implementing Weiskopf and Weng's (2013) conceptual model for data quality, the objective of this article is to provide a practical introduction to secondary analysis of EHR data.

The article describes a pragmatic process. The article is presented as a case study, with examples from an actual study to illustrate common issues found during secondary analyses. Just as in primary research studies, secondary analyses require immersion in the data prior to analyses, with preresearch, data collection, and data quality assessment phases before the main study analyses are undertaken.

Methods

A retrospective pre-post design secondary data analysis of 106,486 inpatient visits over 5 years, in a large academic center (the University of Utah), was conducted to determine the impact of computerized provider order entry on mortality and length of stay. Data from the EHR and from administrative databases were combined to create the research data set. Extensive data quality assessments and data cleaning activities were performed prior to statistical analyses in order to make the data *fit for use*. These efforts provide a unique perspective, using real-life examples, to illustrate issues.

Results

Part I: Preresearch and Data Acquisition

Preresearch Steps

In most organizations, researchers are not granted direct access to EHR data. Reasons include data complexity (e.g., an expert familiar with the databases may be required to locate the desired data elements), regulatory issues including Health Insurance Portability and Accountability Act (HIPAA) considerations, and other security regulations (Curcin, Soljak, & Majeed, 2012; Safran et al., 2007). Therefore, nurse researchers will likely need assistance obtaining the data.

Before requesting data from the EHR, you will need to obtain IRB approval for the study. An important component of the IRB application is to determine the expected number of records in the data set. Consider how selection of hospitals or patient care units, and the study period length (days/months/years), will impact the sample size. Also determine if hospital beds or clinics were added to, or removed from, the institution during the study period as this can affect your choice of which patient care units to include or may account for different sample sizes in pre- and postimplementation phases. The research underlying this case study was a pre-post design study with patient observations within the *patient care unit* as the primary unit of analysis. Therefore, patient care units were only included if the unit existed throughout the entire pre- and postimplementation time periods and participated in the computerized provider order entry implementation.

Several methods can be used to estimate sample size. Use electronic resources at your institution to check hospital statistics. Some institutions, such as the one in this case study, provide web-based tools to assist with preresearch sample size estimates. Given a set of criteria, the tools report aggregate counts of the number of records that meet the specified criteria, without disclosure of individual patient record information. If tools to estimate sample size are not available, then ask others familiar with these data at your institution to help complete this task. Most organizations include a formal mechanism for requesting aggregate sample size estimates as preparation for research. Nursing representatives in the quality improvement department, hospital administration personnel, or information technology (IT)/electronic health record (EHR) experts may be able to help locate the data and assist with sample size estimates.

Once the sample size has been estimated, apply to the Institutional Review Board (IRB) for study approval. IRBs require a precise estimate of the maximum number of observations/patients that will be included in the study. If the query that gathers the clinical data returns more observations than the original estimate, you may need to verify your inclusion/exclusion criteria; or you can amend the IRB application to remain in compliance. Careful preresearch aggregate estimates, combined with systematically overestimating the number of patients/observations that will be in your study (e.g., adding 5% to the aggregate estimate), can prevent violation of the Institutional Review Board agreement.

Data Acquisition

Obtaining the data set includes many steps, for most of which the researcher must rely on others. These steps include determining the potential sample size, specifying the precise demographic and clinical fields desired, and deciding whether or not to include protected health information. For data extraction, the primary *concordance* concern is the extent to which the data in the research data set matches the study's conceptual framework, research questions, and the study protocol. The goal is to ensure the data extracted matches the independent, dependent, and covariate variables intended for use in the study.

Once the IRB has approved the study, place a request with the appropriate data team. This request needs to be precise and explicit. The University of Utah enterprise data warehouse (EDW) team uses a form that contains frequently requested data fields such as age, date of birth, admission date, and discharge date.

Protected Health Information, or PHI, is restricted by HIPAA and other regulations. PHI can be de-identified using Safe Harbor methods; this will eliminate 18 types of data (Health & Human Services [HHS], 2012) such as names, birthdates, and other identifying information. Including PHI in your research data set requires additional steps to preserve data confidentiality, usually by keeping the data set behind secure firewalls and storing the data on encrypted drives. To remain compliant with the ever-changing policies, technology capabilities, and government regulations, frequently check your institution's policies and procedures.

Some data may be stored in multiple alternative places in the database, depending on which practitioner collected and documented the data and when it was collected (Botsis Hartvigsen, Chen, & Weng, 2010; Goodwin et al., 2003). One way to ensure the data received matches the intended data is to provide a screenshot from the EHR. By showing the data field in the context of the EHR, the EDW expert will be able to more easily identify the desired data element in the database.

Another tactic that can facilitate data extraction is to provide the numeric code associated with the data field. Numeric codes can increase processing speed in large databases (Polit & Beck, 2012; Waltz, Strickland, & Lenz, 2005). For example, Figure 5.1 shows codes associated with systolic blood pressure in the local clinical database. You might want the systolic cuff pressure (1172997) and the systolic arterial pressure (57526461) but not the orthostatic, sitting pressure (1172998). Providing a screenshot and/or the numeric data field code is the most efficient way for the data extractor to find the intended data points.

Once the data fields have been identified in concordance with the study design, and the data have been extracted; it is time to evaluate the quality of the data set. Use Weiskopf and Weng's (2013) five dimensions to determine if the data are *fit for use* for your study. Proceed by checking the overall data set, then the demographic variables, and finally the covariates for completeness, correctness, concordance, plausibility, and currency.

Part II: Data Quality Evaluation

Check the Overall Data Set

First check to see if all data are in a format that will be usable and meaningful for analysis. Data may need to be changed from a text format to a numeric field type (some databases store all data as text, even if the actual content is a number). Demographic data often falls into this category, as the items are often coded with numeric indicators. It is easier for the computer to process the number '2' than the text "Native Hawaiian and Other Pacific Islander" (Green & Salkind, 2008). For data fields that are coded, be sure to obtain a list translating the numeric codes to meaningful text.

For this case study, some data originally stored in a date/time format required a

40059	72	57526461	Systolic Blood Pressure - Arterial
40060	72	1172997	Systolic Blood Pressure
40061	72	54442981	Systolic Blood Pressure - Arterial
40062	72	1172998	Systolic Blood Pressure - Sitting
40063	72	1172999	Systolic Blood Pressure - Standing
40064	72	1173000	Systolic Blood Pressure - Supine
40065	72	57514965	Systolic Blood Pressure Invasive
40066	72	202102808	Systolic Blood Pressure Orthostatic
40067	72	166084427	Systolic Blood Pressure post Activity
40068	72	57522166	Systolic Blood Pressure Sitting
40069	72	57522172	Systolic Blood Pressure Standing
40070	72	57522176	Systolic Blood Pressure Supine
40071	72	143990497	Systolic Blood Pressure with Activity
40072	72	57519352	Systolic BP Pediatric Trauma Score
40073	72	186098861	Systolic BP Sitting, Post-Dialysis
40074	72	186098835	Systolic BP Sitting, Pre-Dialysis
40075	72	57520908	Systolic Murmur Description
40076	72	57520934	Systolic Murmur Grade
40077	72	57520696	Systolic Pressure Assisted
40078	72	180199707	Systolic, Left Arm
40079	72	180200305	Systolic, Left Leg
40080	72	186098823	Systolic, Post-Dialysis
40081	72	186098781	Systolic, Pre-Dialysis
40082	72	180200130	Systolic, Right Arm
40083	72	180200523	Systolic, Right Leg

Figure 5.1 – Systolic blood pressure database codes

recode to a yes/no field to be fit for use for our research analyses (we needed to know if the data were present, but not the actual date/time). Such time-related conversions are a *currency* issue. You may consider having the data warehouse expert adjust the extraction query and correct all issues at once, before closing out your data acquisition request. Verifying that data types and formats are correct early in the process provides the opportunity to correct errors early on and hopefully saves time.

Inclusion/Exclusion Criteria

Using Weiskopf and Weng's (2013) five dimensions, examine the data to ensure the inclusion and exclusion criteria have been met. The original data set extracted for this study had issues with *currency*, *concordance*, and *correctness*.

Age produced the first data anomaly found in the case study data set. The age data suffered from correctness and currency issues. Initially, 17 year olds were found in the data set even though the study protocol approved by the IRB was to exclude patients less than 18 years old. Upon investigation, it was found that these patients had turned 18 during the hospital stay. The data extraction query was modified to specify that patients had to be age 18 or older on the day of admission.

A second flaw was discovered with the inclusion/exclusion criteria. This was a problem with *concordance* between the study intent and the data request. An "observation" in the data set represented a unique inpatient visit to any of the organization hospitals. All units were included in the data extraction; however, some units were not appropriate for the research because some units had not implemented CPOE during the study time period. Initial descriptive statistics about the patient care units revealed that the extraction included units that were not desired as part of the research. The extraction query was changed to limit the data set to only the patient care units where CPOE was implemented, instead of all observations with "inpatient" as the patient status. This resulted in a data set that more accurately matched the research questions and study conceptual framework.

Dependent Variable Analysis

Once satisfied that the data set as a whole reflects the needs and design of the study, the next step is to evaluate the dependent variables. High-quality dependent variables are critical to being able to answer the research question. Use systematic analysis of ranges, missing data, mean, median, mode, standard deviation, histograms, box plots, and stem-leaf graphs, to determine if dependent variables (outcome variables) are complete, correct, plausible, timely, and in accordance with the study design.

The above analyses were used to verify data were complete and plausible. All observations had a value greater than 1, and were computed to 2 significant digits for length of stay; values were 0 for alive and 1 for deceased in the mortality column. Simple counts showed much larger number of 0 (alive) than 1 (deceased) patients, findings that verified plausibility.

Next, independent *t*-tests and Chi-square test of independence were performed to assess differences between the pre- and postimplementation phases, and to assess for differences between patient care units. At the time, it was thought these were the correct statistical tests to use for these analyses. However, the results were inconsistent leading the researcher to question the differences. Additional analyses were performed to determine if there were differences between patient care units. These results, for both length of stay and mortality, were also inconsistent, indicating some other factor must be impacting the results. Further analysis showed more than 30% of patients had multiple observations and likely had observations on different patient care units. Multiple observations and/or observations on different patient care units violated the assumption of independence of observations, associated with both independent *t*-tests and Chi-square of independence (Munro, 2005), likely resulting in the inconsistent results. For this reason, hierarchical linear models were used in the final analyses. This issue does not fit neatly into Weiskopf and Weng's (2013) conceptual model, but most closely resembles a concordance issue. In this case, the statistical test used to evaluate the dependent variable was not in agreement with the data.

<u>Demographic Variable Analysis</u>

After evaluating the dependent variables, the demographic variables should be evaluated for the five dimensions to ensure *fitness for use*. In the evaluation of inclusion/exclusion criteria, patients who were 17 years old at admission were removed from the data set. Additional issues of *concordance* and *completeness* were found in the gender distribution and the race and ethnicity variables.

When gender was initially evaluated, the sample included 56% female and 44% male. These results did not match the general local population, which is 50.2% female (U.S. Census Bureau, 2013). Upon further evaluation, it was determined that the sample represented the hospital population, which included labor and delivery patients. Labor and delivery patients were unintentionally included in the query, and accounted for the over-representation of females. Because labor and delivery mortality rates are computed differently than hospital mortality, these patients were excluded from the design. This was a concordance/agreement issue with the study design and consequently, these observations were removed from the sample, which changed the percent of females (50.3%) to be more representative of the general Utah population.

Race and ethnicity data also had data quality issues. The race variable contained 9 possible responses while ethnicity had 11. These demographic variables had completeness issues. For example, four levels of race comprised 18.8% of the sample but had little meaning individually. Missing (2.2%), unknown (11.2%), other (4.7), and patient refused (0.7%) were separately coded, but all represented incomplete data; these were recoded to a single value. The White/Caucasian group comprised 76.3% of the sample, consistent with the state demographic. The remaining 4.9% of the sample included American Indian and Alaska Native, Asian, Black or African American, and Native Hawaiian and Other Pacific Islander. Due to the low percentage of the four remaining groups, they were collapsed together and recoded as People of Color. Descriptive statistics for ethnicity revealed a similar situation. Consequently, ethnicity was recoded to Not Hispanic/Latino, Hispanic/Latino, and Not Reported. *Completeness* and *concordance* both played a factor in recoding race and ethnicity to levels *fit for use* in the final analyses.

Covariate Analysis

After analyzing dependent and demographic variables according to Weiskopf and Weng's framework (2013) perform similar analyses on any remaining covariates or independent variables. Again, use a systematic process to examine the *completeness*, *correctness*, *concordance*, *plausibility,* and *currency* issues with the data. Issues in this case study included data issues with body mass index, nurse hours, patient severity index, and orders.

Body mass index

In the EHR, body mass index (BMI) was not a required part of nurse charting; nor were the associated components of height and weight. On initial extraction, more than 60% of the records were missing BMI (or the components to calculate BMI), a severe incompleteness issue.

There was also no error checking when nurses entered the data into the electronic forms. Height and/or weight data were often incorrectly entered into the HER, resulting in calculated BMI values greater than 10,000. We limited the data set to omit extremely high BMI values. The histogram in Figure 5.2 demonstrates a bimodal distribution of BMI values, after removing the implausible BMI values. Approximately 1,400 observations equaled zero, with several other values that were implausibly low as well. This second *plausibility* issue also doubled as a *correctness* issue. The inclusion of so many BMI values of 0 affected the mean, median, mode, and standard deviation.

Body mass index data had issues with correctness and plausibility. These issues may have been overcome by imputing values, if the number of errors had been relatively small. However, there was no way to compensate for the large number of missing values. Because the hierarchical analyses would exclude the entire record, for observations with a missing BMI value, it was decided to exclude BMI from the final analyses.

Nurse hours

More than 10,000 observations had no value for the nurse hours. However, these incomplete records were not removed from the overall data set and were used in the final analyses. The SAS HPMixed procedure excluded observations with missing nurse hour data, resulting in a sample size of over 89,000 observations, deemed large enough to capture the intent of the study. The SPSS generalized linear mixed procedure calculated an average number of nurse hours and used this average for all observations. This allowed use of the entire data set but caused a minor *concordance*, because it did not match the original goal of using exact number of hours per quarter for each specific nursing unit.

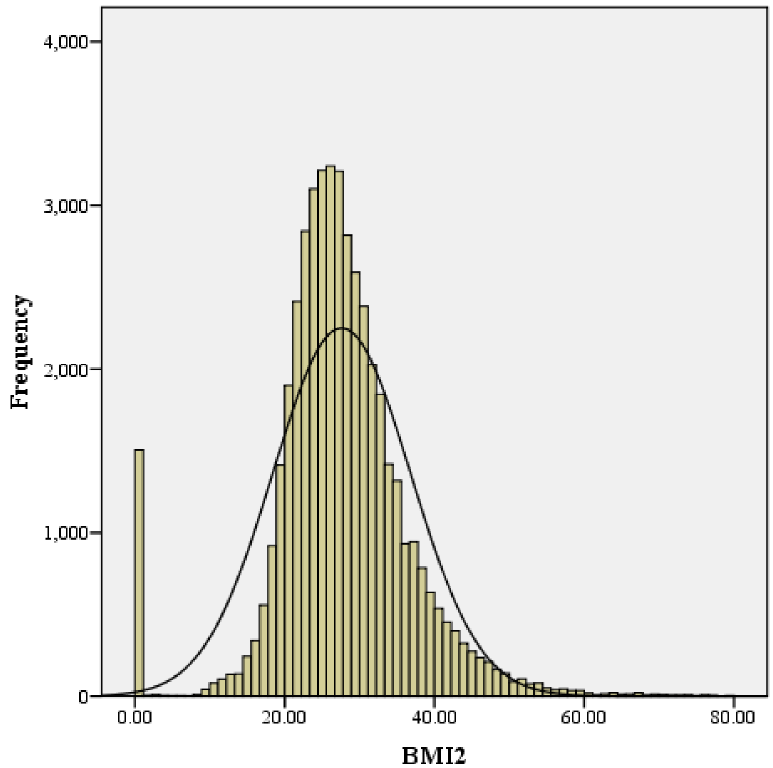

Figure 5.2 –Body mass index distribution

Patient severity index

Like nurse hours, the patient severity index, suffered from completeness issues. Patient severity index was missing from 13,563 observations. In designing the study, the researcher expected that patient severity index would be an objective scale variable. It was later discovered that this was a nominal variable, and the definition of categories varied widely from unit to unit. For this *concordance* reason, patient severity index was excluded from the final statistical analyses.

Orders

When evaluating the descriptive statistics for the number of laboratory, radiology, and medication orders placed for each observation, a *concordance* issue was discovered that would have affected the length of stay analysis. This was discovered in a round-about way by evaluating the number of orders placed for patients.

One patient had an implausible 105,000 medication orders for a 3-day admission. Further investigation uncovered that the researcher had conceptualized an order as something placed by the provider; however, in the HER, each medication *task* was recorded as a separate order. A related, underlying problem was identified during this investigation; the visit status was not automatically updated to “discharged” when the patient went home. The orders-associated tasks continued to be automatically generated until the patient status was changed. This patient had an order for Fentanyl IV every 2 minutes; and the order was not formally discontinued. A new task was generated every 2 minutes for 8 months, thus creating the implausible value of 105,000 medication orders for a hospital stay lasting three days. Similar issues affected 10,270 records in the research data set.

Consequently, these records were removed from the final analyses, because the number of orders was implausible. Luckily, most of patients impacted by this software issue were hospitalized in patient care units that did not have CPOE implemented. In this case, thoroughly examining the covariates prevented the inclusion of over 10,000 errant observations in the final analyses.

Discussion

Using EHR data for nursing research are increasingly common, and the data collection process can be rapid, typically only involving a set of queries performed by the organization’s data warehouse team. However, many researchers underestimate the importance of, and time needed for, data quality assessments and data preparation.

Performing systematic analysis of ranges, missing data, mean, median, mode, standard deviation, histograms, box plots, and stem-leaf graphs for the inclusion/exclusion criteria, the dependent and covariates will reveal gaps in the data and give the researcher an understanding of distributions (Kahn, Raebel, Glanz, Riedlinger, & Steiner, 2012). Using the clinical and statistical relevance found in the analyses can help the researcher to determine appropriate actions: whether level consolidation or recoding can occur, for example, and which variables should be excluded from the final statistical analyses. These steps are iterative and it is important to examine the results, recode as necessary, and re-examine the recoded values. Performing these steps will leave the data prepared for statistical analyses.

Tips and Tricks

Evaluating the research data set for *completeness*, *correctness*, *concordance* (data and framework agreement), *plausibility,* and *currency* (temporal issues) can assist with ensuring reliability and validity during the preresearch, data collection, and data analysis phases of secondary analysis studies.

The tips and tricks listed in Table 5.1 will help alleviate some other problems

Table 5.1. Tips and tricks summary

Rule Number	Rule
1	Check Hardware and Software
2	Keep an Audit Trail
3	Use Caution when Deleting
4	Use Naming Conventions
5	Pay Attention to Data Formats
6	Remember Fundamental Statistical Considerations

encountered when working with EHR data. These tips and tricks are applicable to any analysis, but are particularly relevant to situations using large data sets.

Rule 1. Check Hardware and Software

Large data sets are typically stored on a server that may be separate from the computer where statistical analyses occur. This can cause computer processing problems depending on the computer you use, the type and amount of data, and the internet bandwidth available. In many cases, statistical analyses can take hours to run. For security purposes, you may need to ensure the computer used for analyses is behind your organization's firewall or on an encrypted hard drive. You will also need to ensure the computer has enough random access memory (RAM) and processing speed to accommodate the statistical analyses; which can be much greater hardware specifications than the typical computer. If the intended analyses will consume more than the average laptop or desktop computer can accommodate, consider working with the institution's computing center, if one is available. The institution in this case study, for example, includes a center for high-performance computing. When working with the computer center, you will likely need to go through additional processes to gain access to their servers and/or their building. For this case study, a secure, remote access application (virtual private network) was used to connect to the server; all data and analyses were kept behind the organization's firewall to protect the patient data confidentiality.

Rule 2. Keep an Audit Trail

Data provenance (where the data came from and how the data were processed or changed) is one of the key issues for health data (Curcin, Solijak, & Majeed, 2012). For starters, be sure to keep a copy of the query used to generate the data set. Referring to this query will help you remember the exact data extracted. Ask the data warehouse representative to add comments to the query to assist with translation.

Even with a very large data set, there is the potential for bias caused by which records and variables are selected for inclusion in analyses. An audit trail will help track the data set progression and can be used to generate the inclusion criteria flowchart (Consort diagram), which may be needed when publishing the findings. Tracking the data set progression will make it possible for you and others to recreate the process increasing generalizability, reliability, and validity.

Rule 3. Use Caution when Deleting Rows or Columns

Do not make any changes to the original data set and store the original data set on a secure, encrypted drive. Deleting rows or columns from the original data set is not advised. Instead, create a data subset or recode variables as needed to perform statistical analysis. This can be a helpful strategy that allows the researcher to remove protected health information or create focused subsets, e.g., for review with the statistician. In this study, approximately 15 data subsets were used for preliminary and final analyses.

Recoding variables is used to simplify analyses and in some cases may be required to protect the identity of patients and research subjects. For example, you may need to create a subset then recode protected health information (PHI) variables (e.g., all patients with age > 89 must be grouped together).

Instead of creating subsets (copies of a portion of your data set), it is possible to keep the original data set and run queries to focus on the subsets. This tactic requires advanced structured query language (SQL) skills, however, so build time for learning

SQL into your timeline if this approach is taken. Having a base data set (and a back-up on a different, encrypted drive), creating subsets, and recoding variables into a new variable while preserving the original value, ensures data integrity by providing a starting point and a historical perspective of the data.

Rule 4. Attend to Data Formats

The data format is the type of data the database assigns to the various fields. Data formats include text, numeric, date/time, and others. For example, the data format for race in this case study started as a text field (e.g., “Asian”). Recoding the value changed the text field “Asian” to the number ‘2’. To remember that the number ‘2’ represents “Asian”, use the statistical software “value label” property. This allowed analyses to use the numeric codes, which made processing efficient, but enabled the researcher to create statistical outputs with the more meaningful term of “Asian” (Green & Salkind, 2008).

For this case study, the data set was originally contained in an Oracle database and moved to the statistical software programs SPSS v21 and SAS v9.3. Moving data between the database and the statistical software programs sometimes changed the data format and removed the labels or changed the labels from intuitive text “Asian” to a number. If there is the need to move data between database and statistical software, remember to verify the variable type is correct, the field length did not change, and the labels are present and correct before beginning statistical analyses.

Rule 5. Use Naming Conventions

Creating a naming convention (Green & Salkind, 2008) can help track the progression of the data, track changes to the project, and help ensure reliability and validity. Typical file naming conventions use an underscore (_) or hyphen (-) to make the file names readable, (e.g., File_Name). Numbering the data files will help keep track of the progression, e.g., File_Name_01, but appending the date to the file name will facilitate recall and link the file to the field notes, e.g., File_Name_01-15-2014.

Naming individual fields within the data set requires more considerations. Some databases and statistical programs require all capital letters and most allow no spaces in the name of the field. Create the habit of generating variable names that are descriptive of the contents, and remember that most programs allow you to use an underscore (_) to make the variable names readable, such as RACE_RECODE.

The data in this study, in most cases, went through 2 transformations and consequently 2 name changes. The first change generally recoded the text field to a numeric field. For example, RACE data was originally a text field was represented by "American Indian/Alaskan Native", "African American", etc. In order to use the data in a statistical analysis, the data had to be recoded as a number. Therefore, RACE was recoded to a new field named 'RACE_RECODE', where "American Indian/Alaskan Native" = '1' and "African American" = '2'. Once this task was completed, basic descriptive statistics were run. Often, the results of the descriptive statistics suggested consolidation of some of the categories. For example, it became clear that demographic data for the state of Utah did not support 8 categories of race. Secondly, having 8 race categories was going to unnecessarily complicate the analyses and interpretation of the findings. Consequently, race data were reduced to three levels with the field named RACE_CON: "White/Caucasian" = '1', "People of Color" = '2', and "Not Reported" ='3'. This type of consolidation occurred for most of the demographic variables: age (consolidated to ranges), ethnicity, marital status, and place of residence.

Rule 6. Remember Fundamental Statistical Considerations

Be mindful when considering the types of statistical tests that are appropriate for your data set. This study could not use parametric statistics because some of the data were nested, and the dependent variable, length of stay, was not normally distributed. In this study, nesting refers to patients who were admitted more than once or had visits on more than one patient care unit. In statistical terms, nesting means there is a lack of independence of observations, it can represent repeated observations in the same patient, or other types of clustering. Patients, in this study, were clustered within patient care units; and because CPOE was implemented on a per-unit basis, the patient care unit was the primary unit of analysis. The data considerations in this study suggested the necessity for using hierarchical linear modeling. An alternative approach might have been to restrict the data to a single observation per patient. This path requires the researcher, a priori, determine whether to use the first, last, or random observation. Matching the statistical test with the research questions will lead to valid results (Polit & Beck, 2012). For this study, all observations were included to match the goal of the study: to observe the impact of computerized provider order entry at the hospital level.

Lessons Learned

The final data set in this study was fit for use in the final analyses because the above steps were performed. Five data quality dimensions were evaluated: *completeness*, *correctness*, *concordance*, *plausibility,* and *currency*. Responses to data quality evaluations reduced the overall size of the data set from the initial data acquisition, some variables needed to be eliminated, other variables needed to be recoded or transformed. The resulting data set allowed for robust, high-quality statistical analyses.

"A systematic approach helps increase scientific rigor" (Pryjmachuk & Richards, 2007, p. 53). With an increase in the availability of structured patient data spanning multiple years, the time to research publication should be shorter for secondary analyses of EHR data, compared to primary data collections. Due to the large amount of data, charting errors and errors of omission, software limitations, and the evolving entity that is the clinical EHR database, however, the process of data cleaning may take longer than expected because the data as stored may not be *fit for use* for the particular study. Using the process and rules outlined above may help decrease the time to completion and produce accurate results for researchers who are, perhaps for the first time, working with large data sets.

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CHAPTER 6

MISCELLANEOUS FINDINGS

This chapter reports findings not included in the previous 2 chapters. The chapter includes statistical analysis from the cancer specialty hospital, and details related to the impact of patient orders and patient care unit, on length of stay and mortality outcomes. Lastly, the outcome variables are trended over time, presenting an alternative view of the data that generates new insights and hypotheses.

Specialty Hospital Subset

The cancer hospital included four patient care units: three medical/surgical units and one intensive care unit totaling 50 hospital beds and 10 beds from the general hospital's bone marrow transplant unit for a total of 60 beds. The study dates and times and inclusion/exclusion criteria were the same as the main sample, resulting in a subset containing 16004 visits, 7604 in the pre-implementation phase and 8400 in the postimplementation phase.

Like the analyses for the main findings, code resuscitation activation, rapid response team activation, and palliative care status were removed from the mortality analyses as to not overly influence the results. The cancer hospital only had private rooms, throughout the study time frame, so private room status was also removed from analyses.

Length of stay results

Table 6.1 shows the detail for all patient care units. All of the psychiatric units had a decrease in length of stay. Nine of 10 med/surg units had a decrease in length of stay. Conversely, four of five intensive care units saw an increase in length of stay.

The length of stay model for the cancer specialty hospital subset (Table 6.2) excluded smoking status and nurse hours. These variables were not statistically associated with length of stay and removed in a step-wise fashion.

Table 6.1 Mean length of stay by patient care unit

Patient Unit	Pre	CPOE Mean	Post Mean	Delta
Psych 1	12.53	10.28	10.56	-1.97
Psych 2	6.92	6.1	6.62	-0.3
Psych 3	10.2	12.03	8.93	-1.26
Psych 4	9.9	11.25	8.72	-1.18
Psych 5	13.29	10.04	10.42	-2.87
Psych 6	8.6	6.14	8.2	-0.4
Med/Surg 1	4.91	4.53	4.06	-0.85
MedSurg 2	6.48	6.26	5.52	-0.96
MedSurg 3	4.35	4.51	4.39	0.04
MedSurg 4 (Cancer)	5.55	4.61	4.93	-0.62
MedSurg 5 (Cancer)	4.74	4.48	4.56	-0.18
MedSurg 6 (Cancer)	6.51	7.48	4.63	-1.88
MedSurg 7	13.89	13.52	10.91	-2.99
MedSurg 8	5.31	6	4.84	-0.46
MedSurg 9	4.29	4.4	4.14	-0.14
MedSurg 10	5.4	5.16	5.29	-0.1
ICU 1	14.07	13.86	13.85	-0.21
ICU 2 (Cancer)	13.3	17.56	15.03	1.74
ICU 3	8.31	9.52	9.95	1.64
ICU 4	5.01	3.35	7.17	2.15
ICU 5	11.82	10.32	14.29	2.46
Rehab 1	14.95	13.4	15.36	0.41

Table 6.2 Length of stay and mortality statistical results for cancer hospital

	n	Pre-estimate	Pre-CI	Post-estimate	Post-CI	Decrease in days	*F*	*df* (num, dem)	*p* value
				Length of Stay					
4 units	16004	5.08	3.40, 8.16	4.45	3.05, 6.96	0.93	72.071	1, 15975	< .0001
				Mortality					
4 units	16988	0.005	0.000, 0.096	0.005	0.000, 0.096	0	0.048	1, 16,976	0.827

The analysis for the subset showed a decrease in length of stay of 0.93 days (f = 72.07, $p < .0001$), with a narrower confidence interval (3.05, 6.96) than found with the main findings. As seen with the main findings, the three medical/surgical units in the cancer hospital subset displayed a decrease in length of stay (-0.18, -.062, and -1.88 days) while the intensive care unit had an increased length of stay (1.74 days).

Mortality results

The covariates gender, race, marital status, insurance type, smoking status, and nurse hours were not statistically associated with mortality in the cancer hospital subset, and were removed from the final model in a step-wise fashion. The remaining covariates in the model were age, ethnicity, and admitted via the emergency room. After analyzing mortality using hierarchical linear modeling techniques, no statistical significance was found (Table 6.1), $n = 16988$, ($f = 0.048$, $p < 0.827$). There was no clinical change as the estimated mortality rate in both the pre- and postimplementation phases was 5 per 1000 admissions.

When reviewing mortality at the individual patient care unit, all four units had notable decreases in mortality. Even though there was no statistical difference found in the hierarchical linear modeling analyses, all four units saw a decrease in mortality. Table 6.3 shows the change in the number of deaths. The med/surg units decreased 0.8, 1.0, and 9.5 deaths per 1000 observations. The lone intensive care unit decreased 8.6 deaths per 1000 observations.

Table 6.3. Mortality for patient units at the cancer hospital

	Pre		Post		
Patient Unit	*N*/Total	Percentage	*N*/Total	Percentage	#/1000
MedSurg 4	73/3339	2.19%	78/3691	2.11%	-0.8
MedSurg 5	7/5155	0.20%	4/3967	0.10%	-1.0
MedSurg 6	8/390	2.05%	7/635	1.10%	-9.5
ICU 2	15/539	2.78%	10/520	1.92%	-8.6

Mortality Discussion

The characteristics for the cancer hospital indicated a more homogeneous population than the overall sample. Length of stay results for the subset remained statistically and clinically consistent with the results from the main findings sample (all three hospitals) decreasing by nearly a full day. Conversely, neither statistical nor clinical significance was noted with mortality in the cancer hospital subset even though each patient care unit saw a decrease in mortality rate in the postimplementation phase. The absence of change in this subset likely had multiple influences. Care processes within the cancer hospital are different than the other 2 hospitals used in this study. For example, rapid response team activation was implemented at the cancer hospital before it was implemented at the other medical hospital and may have altered the impact of CPOE on mortality incidences. Also, the range of diseases and procedures is smaller than found in the general hospital.

The individual units in the cancer hospital subset had higher mortality rates than the med/surg in the other hospital units. The pathology associated with cancer may overshadow the impact of CPOE in this population.

Impact of Orders or Orders Utilization

Background

The essence of CPOE is the process of providers placing orders directly into the electronic system. Thus, it was logical to attempt to assess the influence of orders on length of stay and mortality. At all three hospitals, the laboratory, imaging, and pharmacy orders were available in the enterprise data warehouse for both pre and post phases. In the pre phase, laboratory, imaging, and pharmacy orders were placed on paper, but results were posted in the electronic health record via an electronic interface; thus, the presence of a result could be assumed as a surrogate for an order being placed. The post phase consisted of providers, and some nurses, entering laboratory, radiology, and pharmacy orders electronically; thus, orders could be directly assessed. The laboratory and radiology results were automatically posted in the electronic health record via electronic interfaces for both phases of the study. Nurses were electronically notified of new orders and medication tasks beginning June 2007 so this was not a change for nursing staff.

Orders Results

Table 6.4 describes the orders placed for the entire sample. Only pharmacy, lab, and imaging orders were collected in all three study phases. The mean number of laboratory orders was 35.46 orders per patient visit, the median 18, and the mode zero. The mean number of imaging orders placed was 3.37 orders per patient visit, the median one, and the mode zero. The mean number of pharmacy tasks was 147.38, the median 83, and the mode 41.

The number of orders increased in the postimplementation phase. Table 6.5 shows the orders placed in the pre and post phases for laboratory, imaging, and pharmacy. In the

Table 6.4 Laboratory, radiology, and pharmacy orders overall (N = 106,486)

Order Type	Mean	Median	Mode	Std. Dev	Range	Sum
Laboratory	35.46	18	0	69.327	3544	3775761
Imaging	3.37	1	0	7.507	341	358497
Pharmacy	147.38	83	41	251.414	21760	15693547

Table 6.5 Number of orders by study phase (N = 104,153)

Order Type	Pre	Post	% Increase	Pre Mean	Post Mean	% Mean Increase
Laboratory	1,427,657	2,245,120	57	28.74	41.22	43
Imaging	118,115	229,815	95	2.38	4.22	77
Pharmacy	6,768,753	8,545,191	26	136.24	156.88	15
Total	8,314,525	11,020,126	33	167.35	202.32	21

postimplementation phase, there was an increase in every order type; laboratory orders increased by 57%, imaging orders almost doubled (95%), and pharmacy orders increased by 26%. The total number of orders placed in the postimplementation phase increased overall by 33%.

Hierarchical linear models were analyzed. These analyses included all the original covariates and added the number of laboratory, radiology, and medication orders per observation. Covariates were removed in a step-wise fashion if they were not statistically significant.

Table 6.6 shows the results of the individual units decreased by 0.90 days (f = 1129, p <.0001) while the sample grouping patient care units decreased by 0.91 days (f = 971, p <.0001). Table 6.7 displays the results for mortality analyses and shows a decrease

Table 6.6 Statistical results for length of stay analyses including orders

Sample	n	Pre-estimate	Pre-CI	Post-estimate	Post-CI	Decrease in days	F	df (num, den)	p value
22 units	89817	4.57	3.58, 5.98	3.74	2.98, 4.80	0.90	1129	1, 89785	< .0001
5 groups	89817	5.28	3.01, 10.92	4.37	2.59, 8.51	0.91	971	1, 89782	< .0001

Table 6.7 Statistical results for mortality analyses including orders

Sample	n	Pre-estimate	Pre-CI	Post-estimate	Post-CI	Decrease in deaths [c]	F	df (num, den)	p value
22 units [a]	104153	0.008	0.003, 0.026	0.004	0.001, 0.014	4	75	1, 104125	0.00
5 groups [b]	104152	0.006	0.00, 0.087	0.004	0.00, 0.059	2	35.5	1, 104152	0.00

[a] Continuous predictors fixed at the following values: Pharmacy 147, Laboratory 35, Imaging 4
[b] Continuous predictors fixed at the following values: Nurse Hours 12,529, Pharmacy 147, Laboratory 35, Imaging 4
[c] Postimplementation phase n = 54,470

of 4 deaths per 1000 admissions in the individual unit sample ($f = 75$, $p = 0.00$) and a decrease of 2 deaths per 1000 ($f = 35.5$, $p = 0.00$) admissions in the grouped unit sample.

The decrease of 4 deaths per 1000 admissions is higher than the results for the main findings but similar to the results containing rapid response team, palliative care, and code activation. These covariates unduly impacted the impact of CPOE on mortality. It must be considered that the presence of laboratory, radiology, and/or pharmacy orders has the same impact on mortality in these analyses. As noted above, length of stay results were no different than the results from the main findings, again showing length of stay is a more stable outcome variable.

Limitations in the Orders Analysis

Operationalizing orders between the paper and electronic format was more difficult than conceptualizing them. Orders are placed and enacted upon to help diagnose and treat conditions. Retrieving orders from the electronic database requires an understanding of the different order types. Pharmacy orders are electronically stored in a different manner than laboratory and radiology orders. Laboratory and radiology orders are generally one-time orders, as opposed to medications, which can be one-time, scheduled, PRN (as needed), or infusion types. Medication orders were recorded in the clinical database based on nurse tasks, not by the parent order. Most medications have multiple tasks associated with the parent order. Individual laboratory tests contained in laboratory panels were unable to be distinguished and possibly caused an under representation of laboratory orders in both the pre and post phases. Radiology orders in the electronic format included separate orders based on laterality (left, right or both), which partially explains part of the 95% increase in the number of radiology orders in the postimplementation phase. In addition, radiology orders were canceled/reordered, making it difficult to differentiate between discontinued and never performed exams and ordered and performed radiology exams in the enterprise data warehouse.

Another limitation of the orders analysis is reflected in the way orders were collected in the pre- and postimplementation phases. Orders in the pre phase were written on paper and faxed to the ancillary system. Most orders in the post phase were placed into the electronic health record by the medical providers with the remaining placed by nursing staff. There is no way to clarify or verify orders placed on paper in the pre-implementation phase. Only the result from the ancillary system was captured, making it possible the increase in number of orders in the postimplementation phase was because the electronic system better captured the number of orders.

A third limitation was the exclusion of order sets from the analyses. Future studies focusing on orders will need to include these complex groups of orders. Finally, this analysis was restricted to number of orders actually placed, but did not attempt to detect order errors or potential errors, which might have been detected prior to the order being placed. One of the proposed benefits of CPOE is to prevent errors and intervene before orders are submitted (Bates, Kuperman, & Teich, 1994).

Orders Discussion

The goals for this subset of analyses were to obtain a baseline picture of the impact of orders in the postimplementation phase and to determine if including orders as a covariate had any impact on length of stay and mortality outcome measures. Unlike other studies (Mekhijan et al., 2003) that showed a decrease in the number of orders, this study showed the number of orders increased in the postimplementation phase. In the electronic system, radiology orders were placed using a "canceled and re-ordered" status, resulting in an artificially inflated number of radiology orders. This status indicator was not retrieved in the data set. This reasoning, however, does not explain the increase in the number of orders for medications and laboratory orders. It is possible the introduction of order sets served as a variation of decision support, prompting providers to place more orders in support of the specific disease process.

Length of stay decreased in the postimplementation phase even with the three additional order type covariates added to the analyses. Length of stay appears to be a stable outcome measure, not unduly influenced by orders.

Like covariates in previous analyses, orders proved to have some impact on mortality analyses. The mortality results from the model containing orders were larger than the results in the main analysis. It is possible orders have the same potential conflict of explanatory covariates acting as intermediate outcomes (mediators or moderators) as did palliative care status, code activation, and rapid response team activation. In the main findings, these variables unduly emphasized the impact of CPOE on mortality (apparent decrease in mortality was unrealistically large). These results indicate the need to view mortality incidences and rates from multiple viewpoints to prevent overstating results.

These analyses demonstrated the pragmatic problem of tracking paper orders, the complexity of electronically storing, and measuring different order types. These findings suggest the need to enumerate and evaluate orders in a separate study. Future studies need to consider how orders are electronically stored before analyzing the impact on patient care outcome measures. Future studies also need to consider order set utilization when evaluating patient care orders.

Unit Effect

After evaluating and comparing statistical models, one constant thread was seen throughout. There seems to be a "unit effect" associated with the outcome variables. This "unit effect" may explain why previous studies have shown contradictory results.

Unit Effect on Length of Stay

Variability was found when evaluating length of stay for the patient care units (Figure 6.1). Psychiatric units saw a decrease in LOS ranging from 0.30 days to almost 3 days (2.87). Nine of 10 medical surgical units experienced a decrease in LOS ranging from 0.10 to 2.99 days. One med/surg unit saw a negligible increase of 0.04 days. Conversely, four of five ICUs saw an increase in LOS ranging from 1.64 to 2.46 days. The fifth ICU saw a decrease of 0.22 days. The rehabilitation unit LOS increased from 14.95 days to 15.36 days, an increase of 0.41 days.

Unit Effect on Length of Stay Discussion

Some trends were noticeable when evaluating length of stay at the patient care unit level. The psychiatry patient care units saw the largest overall decrease in LOS, the ICU length of stay increased and the med/surg units generally decreased. CPOE appears to have facilitated earlier patient discharge with psychiatry patients and most of the med/surg patients, but more detailed reasons for these associations can only be hypothesized. It is possible order sets prompted physicians to order toxicology screens for the psychiatric patients in a timelier manner or that once the orders were placed, the lab turn-around time decreased (Mekhijan et al., 2002). Perhaps discharge medication reconciliation was facilitated by having all the medications in the patient's chart. It would

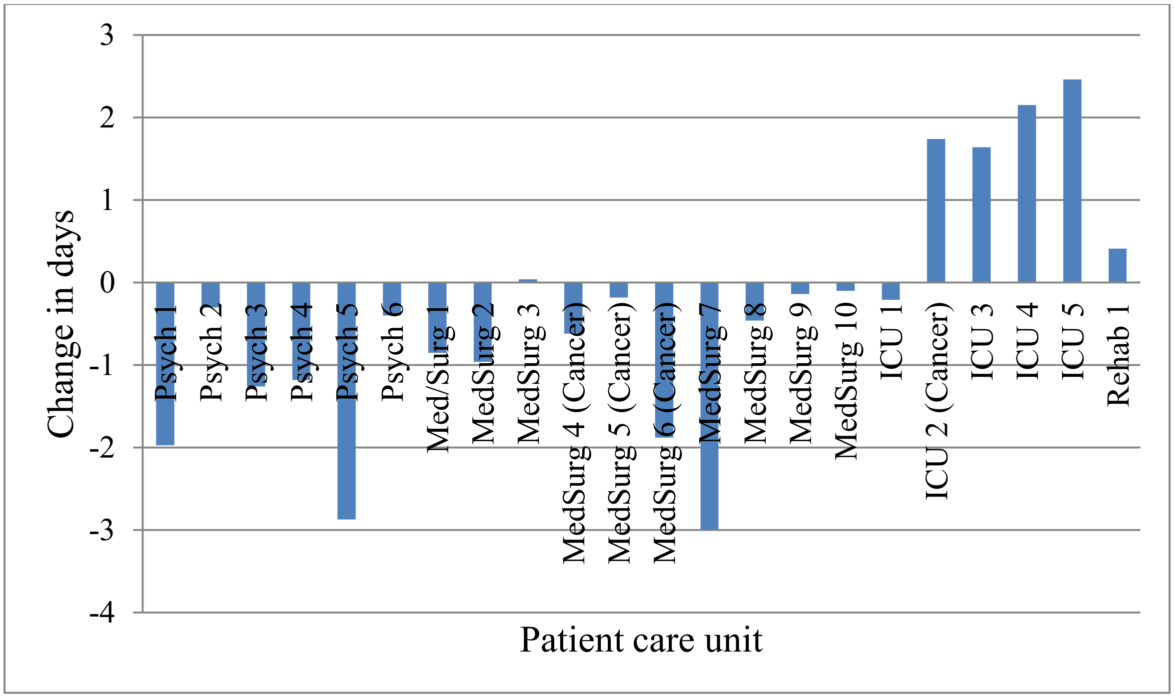

Figure 6.1. Changes in length of stay by patient care unit

be interesting to assess the length of stay changes after the medication reconciliation software component was installed in April 2012.

The increase in LOS in the intensive care units generates its own questions. Further analysis needs to be performed to determine if there were structural changes, for example, if there were significant personnel changes or if the physical layout of the patient care unit changed. Using a patient severity index may have helped determine if patients were more acutely ill during the postimplementation phase. And, it is possible clinicians over-treated the patient due to the presence of order sets. It seems unlikely that clinicians would have had difficulty finding and trending basic clinical data since all components, except CPOE, had been implemented for approximately 2 years, but this may explain why, for some intensive care units, the LOS increased. It is also possible that the increased stay in the ICU, coupled with decreased stay in medical surgical units, reflects patients being moved into the ICU from units sooner (perhaps from rapid response team activation) or other hospital processes, policies, or procedures.

Of the nine studies used to inform this research, 2 reported an increase in length of stay, three had mixed results regarding length of stay (some units increased and some decreased), and four did not assess length of stay. This study indicates there is likely a unit effect with regards to length of stay, perhaps explaining in part the mixed findings from the other studies. Replicating this study at academic and community institutions will help determine if there is a consistent unit effect on the outcome variable length of stay.

Unit Effect on Mortality Results

Figure 6.2 demonstrates the “unit effect” for mortality incidences. The psychiatric patient care units only had one death during the entire study, which occurred in the pre-implementation phase. Mixed results were found in the med/surg units as wells as the intensive care units. Eight of 10 medical surgical units experienced a decrease in mortality of 0.8, 1.0, and 9.5 per 1000 admissions. The remaining 2 med/surg units had strikingly different results, increases of 20.2 and 22.7 per 1000 admissions. Likewise, the ICUs had extreme fluctuations in the number of deaths per 1000 admissions. Three ICUs had a decrease in mortality rate, -8.6, -14.2 and, -191.4, while 2 increased by 12.1 and 45.9. The range for all intensive care units was -191.4 to +45.9, a range of almost 250 deaths per 1000 visits. The inpatient rehabilitation unit had a negligible increase of 0.4 deaths per 1000 visits.

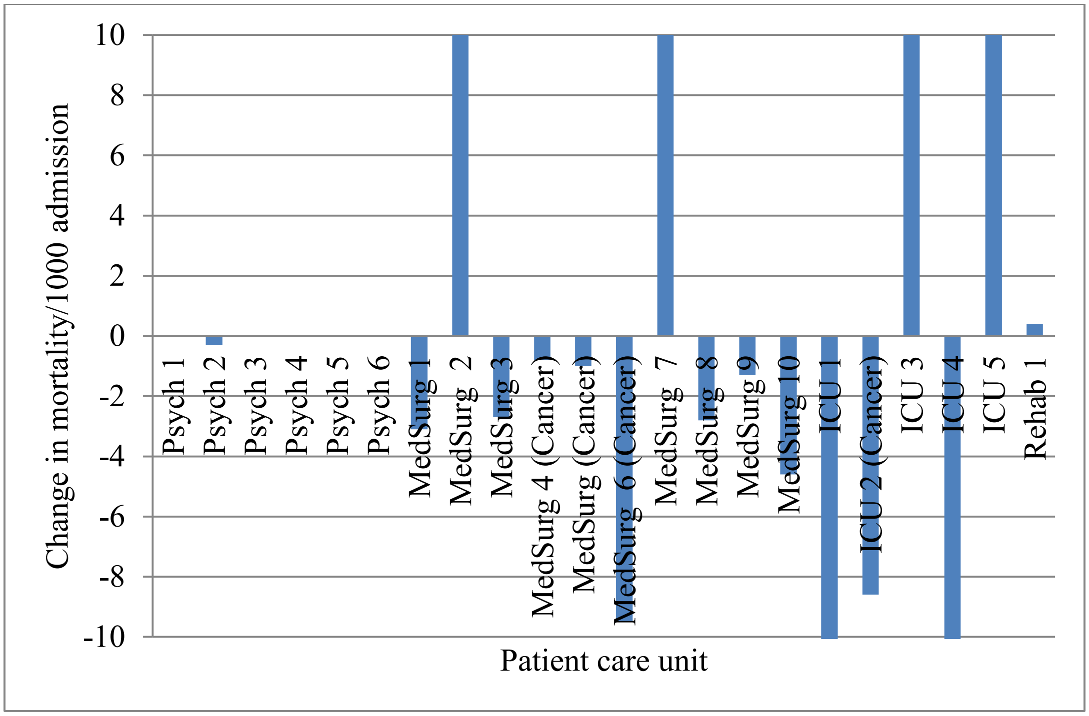

Figure 6.2. Post-CPOE change in mortality by patient care unit

Unit Effect Mortality Discussion

One conclusion that can be drawn from this portion of the analysis is that mortality, in addition to being unduly impacted by many demographic, structure, and process variables, is somehow impacted by the patient care units. In order to determine the impact at the unit level, more analysis needs to be performed. Providing ongoing trended data for each patient care unit may help them identify and resolve causes for the variability. Like length of stay, these results generate more hypotheses than answers and need further analysis.

Intensive care unit deaths were expected to be higher than med/surg units in this study because patients were usually transferred to a med/surg unit before they went home. However, a range of almost 250 deaths per 1000 visits in the ICUs seems extraordinary. Even more so than length of stay, the discrepancy in mortality results between patient care units needs to be questioned and explored further. Suggestions for future analyses include checking for structural variables, such as nursing manager, medical director, or physical layout changes or changes to nurse allocated hours. This study controlled for nursing hours but the mixed linear statistical test used the mean nursing hours and not the exact number of nursing hours per patient care unit. Further analysis could be performed to determine the impact of nursing hours on mortality between patient care units. Adding patient census or nurse to patient ratio may also help understand the unit effect. Other considerations include analyzing orders, order sets, and admission and transfer patterns for specific patient care units. For example, patients in ICU4 may have been cautiously admitted and discharged home instead of being transferred to the step-down unit and then discharged home. Perhaps patient populations and treatment of patients in each population are so vastly different it is not worthwhile to compare between units or groups of units. Mortality may be an integral part of understanding differences between patient care units.

Wide ranges were found with mortality incidences within groups of units and between units. Mortality incidences statistically and clinically decreased in the orders model (216 fewer deaths in the postimplementation period), but there was no change in the number of deaths at the cancer hospital. Wide ranges were found when comparing individual patient care units (-191.4 to 45.9). When comparing grouped units, the med/surg ranged from -4.6 to 22.7 while the ICUs ranged from -191.4 to 45.9 deaths per 1000 admissions. The psychiatric units had only one death for the entire study and it occurred in the pre-implementation phase. The rehabilitation unit had an increase of 0.4 deaths per 1000 admissions. This “unit effect” matters because it demonstrates the instability of mortality between patient care units. The “unit effect” hypothesized in these results could explain, in part, the mixed findings of previous studies.

Trending Outcome Variables

Background

Additional analyses involved trending the outcome variables length of stay and mortality over the study period. The intent of this strategy was to view the data from a different perspective. Data visualization can help researchers to explore, understand, and communicate their understanding (Oxford Consultants for Social Inclusion [OCSI], 2009) of the data.

In this study, data were divided into 3-month portions, a quarter year, and graphed. All points represent beginning to end of a fiscal quarter, e.g., October – December. The first quarter contains days from October 1st until December 31st, 2006. The following quarters form the pattern for the entire study: January 1st through March 31st, April 1st through June 30th, and July 1st through September 30th. Quarter 10 lasts through March 30th. Quarter 11 would have originally contained April and May of 2009, but these months were excluded due to the pilot implementation on April 18th and the main implementation on May 1st. These months are considered the CPOE implementation phase. Consequently, quarter 11, immediately following CPOE implementation, contains an extra month and lasts from June 1st to September 30th, 2009. The 4th month was added to quarter 11 to facilitate seasonal comparisons over the course of the study. Quarters 4, 8, 11, 15, and 19 indicate medical/surgical physician residents’ arrival in July.

Trending Length of Stay Results

Figure 6.3 shows the mean length of stay by quarter using the sample with 100,159 observations. The mean LOS for all patient care units in the first quarter was 6.17 days. The 19th quarter, the second to last quarter evaluated, had the lowest mean length of stay with a value of 5.6 days. The largest spike came during the pre-implementation phase (8th quarter) and was 6.4 days. Three other spikes occurred in the 15th (6.1), 17th (5.9), and 20th (5.75) quarters.

The number of admissions continually rose over the course of the study. Quarter 1 had a total of 4512 visits. The 11th quarter, the quarter immediately following CPOE implementation, had the largest spike and totaled 6612 visits partly because it included a 4th month. Quarter 20 (5393) had slightly fewer visits than quarter 19 (5587). Another way to view the data is to compare the number of admissions with the increase or decrease in length of stay.

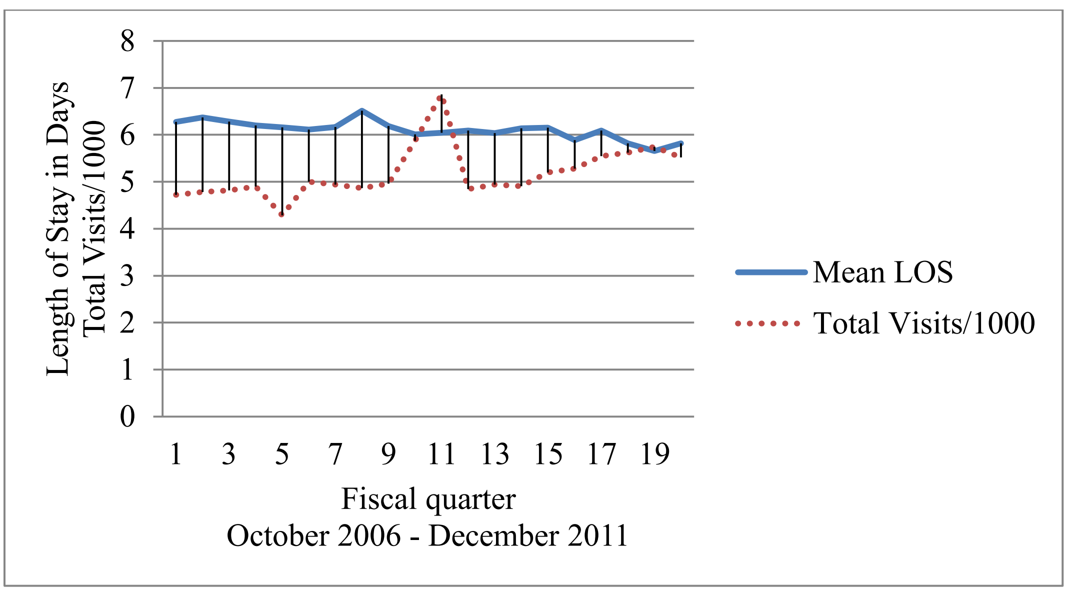

Figure 6.3. Length of stay and admissions trended over the study

Quarter 15 had an increase of 300 observations, yet the average length of stay decreased, on average, 2.4 days. Quarter 17 saw an increase of 260 observations and the average length of stay increased by 2.1 days. There is no repeatable pattern related to the number of admissions increasing and the average length of stay increasing. Each implementation phase had quarters where the number of admissions increase and the LOS increased or decreased. Additionally, each phase saw the number of admissions decrease and the LOS increased or decreased. There appears to be no set pattern for the variation between the quarters when viewing the data out of context.

Seasonal patterns were observed for length of stay data and no repeatable patterns were noted. Spikes occurred (Figure 6.3) in summer quarters, 8 and 15, as well as winter quarter 4. Quarter 8 had the largest spike in the pre-implementation phase of 6.51 days. Quarter 17 had a spike of 6.09, almost a half day less (0.42 days) than the spike in quarter 8. Quarter 19 had the lowest length of stay (5.58) in the postimplementation phase for the summer months, despite an increase in the number of visits.

Trending Length of Stay Sentinel Events

For the purpose of this study, the term "sentinel events" is defined a notable system-wide event, and was either the arrival of new physician residents or the system-wide implementation of any portion of the electronic health record. Sentinel events is not to be confused with The Joint Commission's (2013) definition of sentinel event: an unexpected event causing harm or death to a patient.

Quarter 3 represents the three months prior to implementation of electronic nursing documentation and quarter 10 represents the three months prior to CPOE implementation. There was no associated length of stay increase at either quarter 3 or quarter 10. These findings suggest the nursing staff and the rest of the hospital system were not disrupted enough to impact the length of stay in an upward trend.

Figure 6.4 shows the physician residents' arrival demarcated by the red arrows above quarters 4, 8, 11, 15, and 19. After the physician residents' arrival, there was an increase in length of stay in quarters 8 (0.34 days) and 15 (0.17 days). Conversely, length of stay decreased from the previous in quarters 4 (0.12), 11 (0.12), and 19 (0.16) after physician residents' arrival.

Length of stay spiked once during each study phase when the physician residents arrived (quarters 8 and 15). In quarter 8, before CPOE implementation, the number of visits decreased, yet the average LOS climbed by 0.34 days. In quarter 15, visits increased by 302 and the average LOS increased by 0.17 days, half the increase observed in quarter 8.

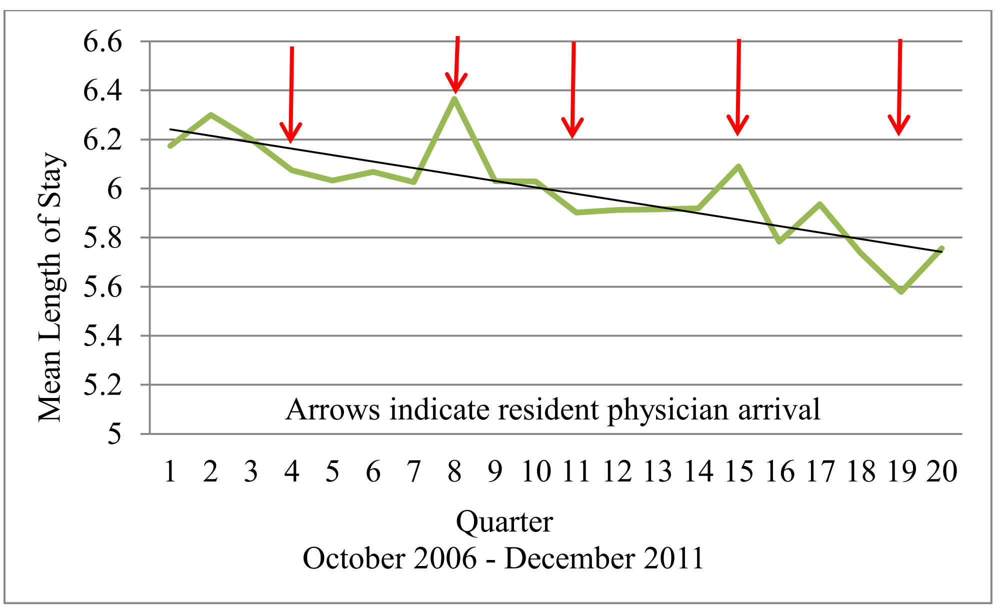

Figure 6.4. Physician resident arrival and length of stay

Trending Length of Stay Discussion

Trending the data showed mean length of stay decreased over the course of the study even while the number of admissions steadily increased. This finding is consistent with the decreasing length of stay trend of the last 50 years (Organisation for economic co-operation and development [OECD], 2013). A study performed by Kalra, Fisher, and Axelrod (2010) showed a steady decrease in length of stay over a 13-year span for internal medicine patients at an urban hospital. Their study also showed an increase in both 30-day and 12-month re-admissions, neither of which was evaluated in this study.

While the decreasing length of stay phenomenon is not new, there are other potential reasons for the decrease. Other potential events that may have contributed to the decrease length of stay are payment changes from both private insurance companies and the Centers for Medicare & Medicaid Services (CMS) as well as improved in-hospital disease management, home-care services, skilled nursing, and rehabilitation facilities. With the invention and availability of the internet it is possible for patients to have improved information access.

The trends described above demonstrate the need to look at the data from more than one perspective to get the full understanding of the impact of CPOE on length of stay. Further research using re-admission data needs to be conducted to determine any relationship between CPOE implementation, length of stay, and re-admission rates.

Trending Mortality Results

Trending mortality incidences over the course of the study showed findings consistent with the main analyses found in Chapter 4. Mortality incidences fluctuated over time and increased over the course of the study (Figure 6.5), but the mortality rate

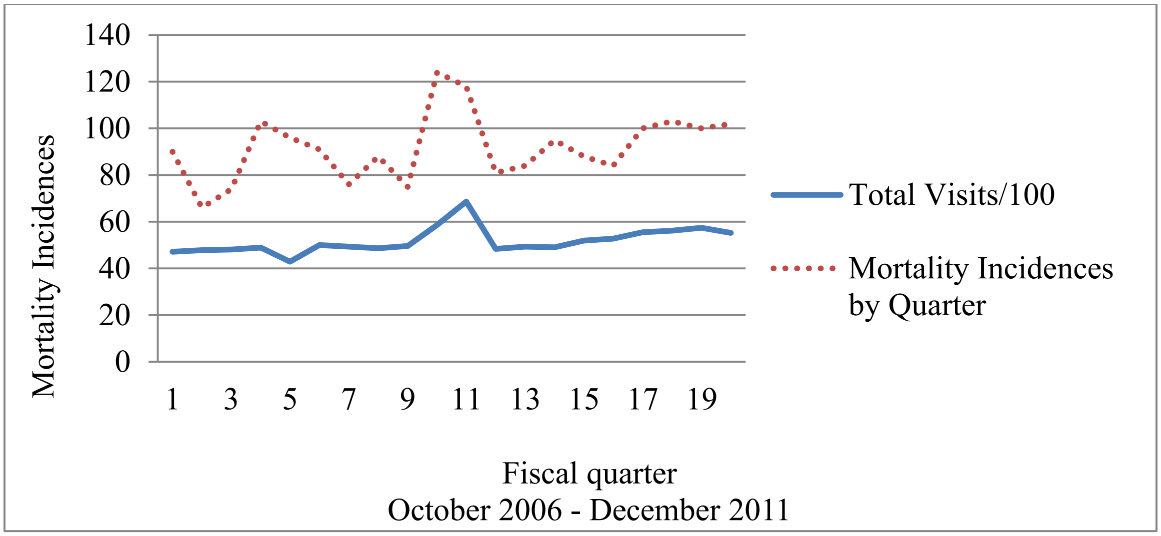

Figure 6.5. Mortality incidences and total visits by quarter

decreased from 1.78% to 1.75% between study phases. The largest spikes occurred in quarter 10 (124), prior to CPOE implementation, and quarter 11 (118), which contained four months. Like length of stay, the number of patient admissions steadily increased over the course of the study as evidenced when quarter 1 had 4723 admissions and quarter 20 had 5522 admissions.

Figure 6.6 graphs the fluctuation in the mortality rate per 1000 observations between the pre- and postimplementation phases. In the pre-implementation phase, quarter 2 (13.8) registered the lowest value and quarter 5 (22.4) registered the highest. Quarter 10 (21.1), the quarter prior to CPOE implementation, had the largest spike for the entire study. In the postimplementation phase, there was an immediate decrease in quarter 11 (17.2) but an upward spike in quarter 14 (19.4). The lowest mortality rate in the postimplementation phase occurred in quarter 16 (15.9).

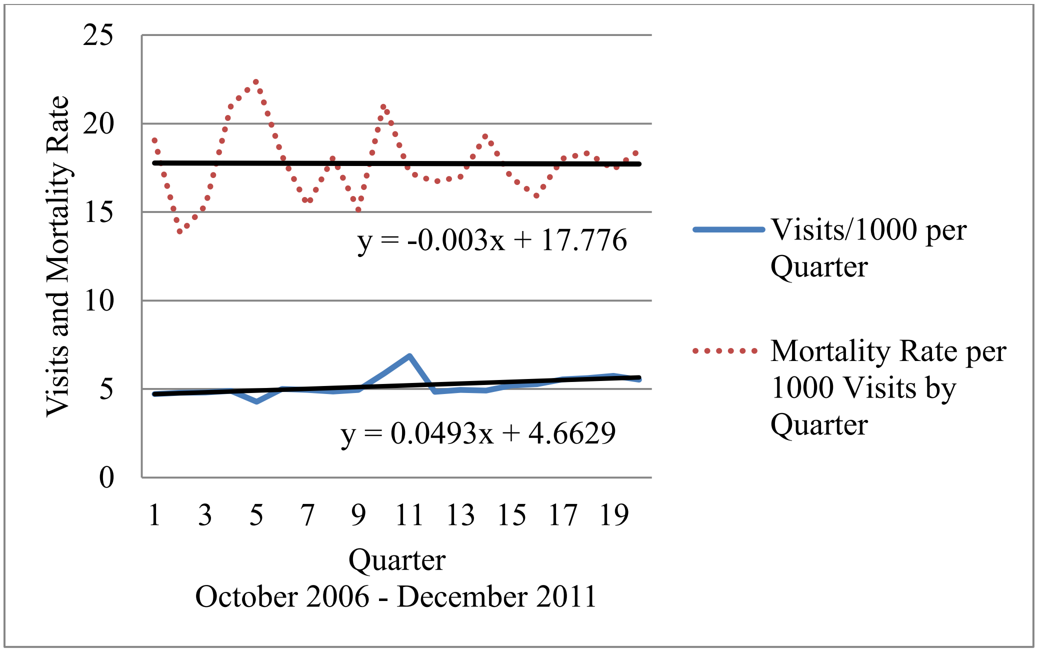

Figure 6.6. Trending mortality rate and patient visits

<u>Trending Mortality Sentinel Events</u>

Figure 6.7 shows the complexity of analyzing hospital system level data by including sentinel events. The blue line displays the fluctuations of the mortality rate over the course of the study. The black lines represent the range of mortality indices over the course of the study. The range for mortality rate is noticeably smaller during the postimplementation phase. This graph does not display the number of admissions but these must be noted in this section. There were 900 more observations between quarters 9 and 10 (in the pre phase) when the mortality rate jumped from 15.12 to 21.11. Quarter 10 had the largest spike in deaths between any 2 quarters for the entire study. However, the increase in number of observations may not fully explain the increase in mortality in quarter 10.

The black arrows identify the quarters immediately preceding 2 EHR related sentinel events: nursing documentation implementation (quarter 3) and CPOE

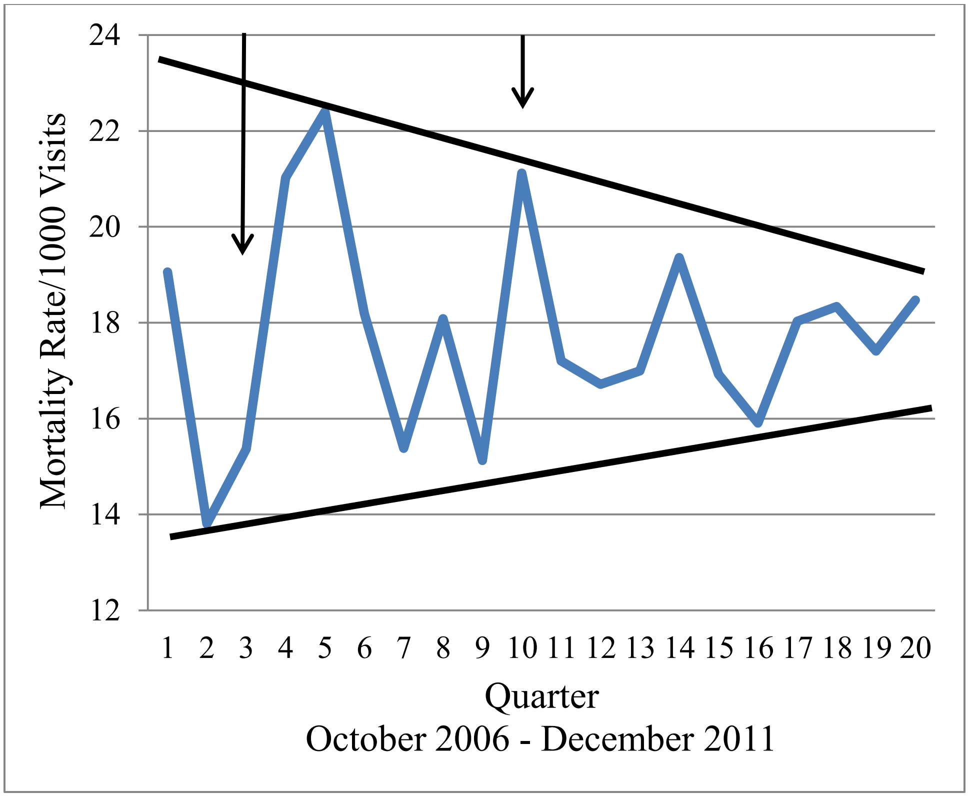

Figure 6.7. Trending mortality range with EHR implementation

implementation (quarter 10). Quarter 3's increase of 1.56 deaths is almost ¼ less than the increase seen in quarter 10 (5.98). The increases in quarters 3 and 10 were accompanied by increases in the number of admissions. These findings suggest the hospital system is disrupted during the lead-up to large-scale implementations.

Trending Mortality Physician Residents

Figure 6.8 shows 5 red arrows pointing to the quarters representing July 1st through September 30th. Quarter 11 includes 1 extra month. These quarters correspond to the arrival of physician residents. In the pre-implementation phase, mortality increased during both quarter 4 (5.66) and quarter 8 (2.71). In the postimplementation phase, quarters 11 (3.92) and 15 (2.44) show marked decrease in mortality rate while quarter 19

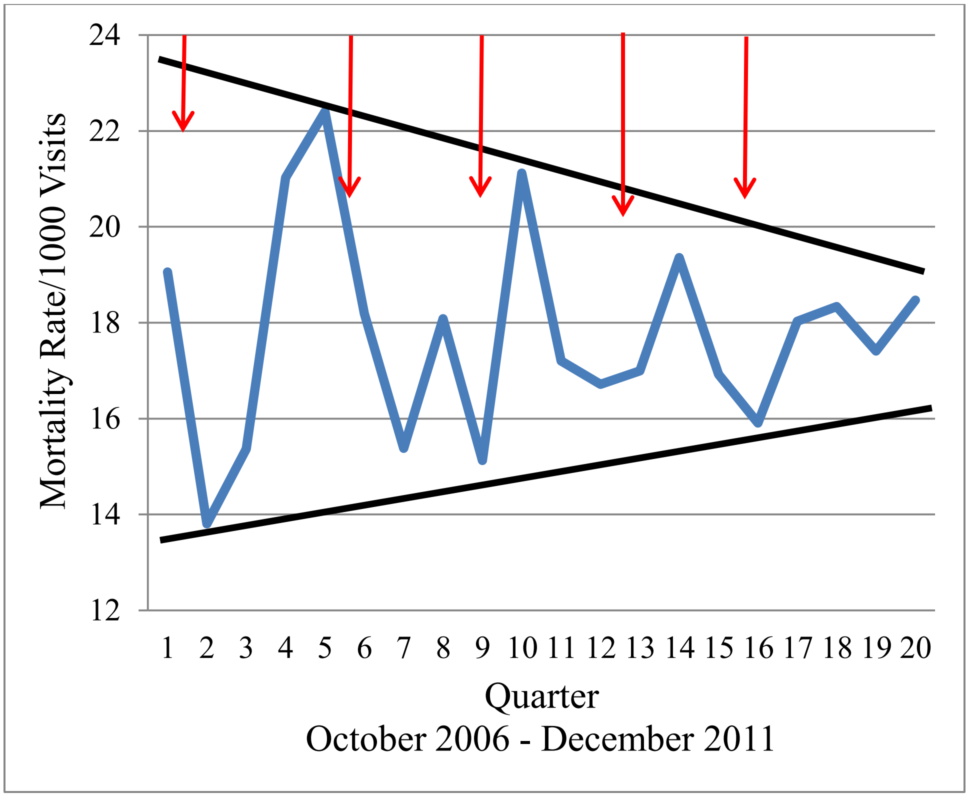

Figure 6.8. Trending mortality range with physician resident arrival

shows a slight increase from 18.03 to 18.33.

Trending Mortality Discussion

Graphing allowed patterns over time to be visualized and correlated with system-wide events. Mortality showed more fluctuation than length of stay during the study. The fluctuations occurred in different quarters than the fluctuations noted with length of stay. No seasonal repeatable patterns were noted. Two patterns, however, were noted. The first pattern involves the quarters before nursing documentation (quarter 3) and CPOE implementation (quarter 10). The second pattern relates to the arrival of physician residents. The electronic health record components in quarter 3 consisted of nursing documentation, and medication tasks posting to the electronic medication administration record (EMAR). Quarter 10 represents CPOE implementation.

The spikes in mortality in quarters 3 and 10 suggest a relationship between the activities and distractions related to implementing portions of the electronic health record. During the implementations at this institution, training took place in the three months preceding the implementation. To ensure nurses attended training, nursing schedules were adjusted, communication was increased, and plans for the implementation were discussed. These findings suggest the disruptions have an impact on patient outcomes.

Future studies need to be performed to determine the impact of electronic health record implementation on nursing care and patient outcomes. Other nursing quality measures could be included to determine if a relationship exists between pre-implementation disruptions and patient care outcomes. Tracking central line and urinary tract catheter-associated infections quality measures as well as medication errors may help determine if this issue is at the nursing level or if the entire system is impacted. Tracking quality measures for entire system could mean exploring dietary, pharmacy, respiratory, and radiology departments. Based on the isolated implementation strategy used during this study, it appears that nursing care, and consequently patient outcomes, were impacted by the disruptions associated with electronic health record implementation.

Another new finding involved the arrival of the physician residents and mortality rates. In the pre-implementation phase, the number of mortality incidences increased during the quarters (4 and 8) corresponding to physician resident arrival. In the postimplementation phase, mortality decreased in all three quarters (11, 15, 19) despite an increase in number of admissions and the presence of new resident physicians. CPOE implementation appears to have a downward impact on the patient mortality rates with regards to physician resident training.

One possible explanation for the decrease in mortality in the postimplementation phases corresponding to new physician residents relates to the number and quality of order sets created for this implementation. Three hundred and fifty order sets were created, many of them disease-specific. It is possible expert creation of the order sets provided structure, and reminders, for the new physician residents. If the physician residents ordered disease specific tests the first time they saw the patient, then it is possible differential diagnoses were confirmed earlier in the patient's disease process and consequently resulted in faster, appropriate treatment and reduced mortality.

Trending the data and overlaying sentinel events provided a view not seen using complex statistical analyses. This view illustrated patterns with mortality not previously seen with electronic health record research. This phenomenon needs to be studied at other academic institutions to determine generalizability. In addition, other institutions need to be aware of the potential disruptions created prior to electronic health record implementation and that this chaos may impact nursing staff as they represent the first, last, and most frequent contact with patients.

Trending Length of Stay and Mortality Conclusion

Trending length of stay and mortality over time helped reinforce the results in the main findings. Additionally, new discoveries were made when layering sentinel events over the chronological graphs. To review, the number of admissions increased over the study period, but the outcome variables, length of stay, and mortality reacted differently to this trend and fluctuations in admissions.

Length of stay steadily decreased over time and there were fewer fluctuations with the range. Length of stay range was not repeatedly influenced by season, other electronic health record implementation, or the arrival of physician residents. These findings suggest the hospital system is better able to absorb seasonal, electronic healthcare record implementation, and physician resident arrival changes without adversely impacting or increasing the length of stay.

Unlike length of stay, mortality seems to be influenced by a number of factors. Recall mortality was unduly influenced by three covariates, rapid response team activation, code resuscitation activation, and palliative care status. In this study, mortality incidences (the raw number of deaths) along with the number of admissions increased over time, but the mortality rate (proportion of deaths compared to number of admissions) decreased slightly over time. Most notable were the fluctuations between quarters. The ranges for the fluctuations were smaller in the postimplementation phase, indicating CPOE had some impact on mortality rates.

When reviewing the trended data with sentinel events, other electronic component installation, and new physician resident arrival, some patterns were noted. Mortality rates increased in the quarters preceding nursing documentation and CPOE implementation. Preparation for large-scale implementation seems to impact the hospital system, including nursing and ancillary staff. Generally, the quarter preceding implementation involves much activity related to the upcoming go-live. Super-users and staff are trained; go-live schedules are created, often including predetermined overtime; information is distributed at the hospital and patient care unit level via email, posters, and web pages. There are many distractions occurring during the pre-implementation quarter in addition to the regular goings-on of hiring and orienting new staff, shifts in census, and caring for patients. Perhaps the additional disruptions impact nursing and ancillary staff, and ultimately patients, more than expected.

In the pre-implementation phase, increases in mortality were noted with the arrival of the new resident physicians. This finding was not repeated after CPOE implementation, indicating an unexpected consequence of CPOE. CPOE implementation appears to have decreased the impact of the new physician residents on patient mortality in this academic institution. Perhaps the presence of 350 disease-based order sets prompted the physician residents to spend less time looking for medication dosages or prompted them to include laboratory or imaging orders they may have otherwise omitted. These 2 components, combined with the decreased turn-around time associated with CPOE implementation, had the potential to impact mortality.

Mortality increases appear to be independent of hospital census in this study. However, mortality appears to be impacted by certain covariates and disruptions to the hospital system. Perhaps the hospital *structure* requires time to adjust to both increases and decreases in the number of admissions and system-wide disruptions. Length of stay, however, does not appear to be as sensitive an outcome variable with regards to covariates included in and events taking place during this study.

Admitted via the Emergency Department

An additional finding was noted when only three covariates remained in the cancer hospital mortality analyses. The variable, admitted via the emergency room, remained statistically significant in the cancer hospital subset as well as the main models (p <.0001). This covariate was not significant in the model that included number of orders (p= .5127). Of note, the emergency room implemented CPOE in October 2009. No statistical adjustment was made to accommodate the different implementation times. Further research needs to be conducted to determine the relationship between patients being admitted via the emergency room and increased mortality.

Miscellaneous Findings Conclusion

The results from his chapter included simple and complex analyses of additional data subsets. Percentages and complex statistical monitoring were used to evaluate the cancer hospital subset (with only private rooms) and another that contained laboratory, radiology, and pharmacy orders. The “unit effect” analyses were evaluated using percentages and graphs. Admitted via the Emergency Department, a possible surrogate measure reflecting the urgency of patient illness was also evaluated. Simple data visualization was also examined as a way to reinforce and understand the statistical findings. Overlaying graphs with sentinel events provided new insights.

Length of Stay

Like the results found with the main findings, the analyses performed on the cancer and orders subsets showed a statistically and clinically significant decrease in length of stay of at least 0.90 days. Trending the data over time showed a similar decrease in length of stay. Conversely, mixed results were noted between patient care units. The consistency of the length of stay results for the main findings and the subsets suggests that length of stay is a consistent outcome variable even after challenging it with multiple confounders and sentinel events. Secondly, CPOE appears to have had a positive impact on length of stay when looking at it from a system standpoint.

Mortality

The mortality analyses differed between the cancer hospital and the main findings. There was no decrease in mortality with the more homogenous cancer hospital subset. The staff used paper-based order sets in the pre-implementation phase so it is possible that cancer hospital staff were more comfortable with order sets in the electronic system. In addition, the cancer hospital has different operating procedures and staff structures, and this hospital implemented the rapid response team sooner. It is possible the nature of the sample, cancer patients, and the different structure components were not disrupted by the sentinel events and, therefore, did not impact the mortality results.

Trending mortality over time illustrated the fluctuations over the course of the study. The number of deaths increased as patient admissions increased, but deaths increased at a slower rate than admissions, overall, resulting in a slight overall decrease for the length of the study. More studies need to be performed to determine if the results in the main findings can be replicated and whether mortality should be used as an outcome variable in CPOE studies. The orders subset showed both clinical and statistical significance with mortality evaluations, similar to the main findings, but possibly overestimated. The unstable results suggest that mortality is a sensitive outcome variable when used to evaluate CPOE implementation.

Overlaying the mortality trending graph with sentinel events generated new information regarding the impact of system-wide disruptions. These data indicate a hospital system was less flexible with regards to disruptions preceding system-wide electronic health record implementation. In addition, the arrival of new physician residents, a disruption before CPOE implementation, was mitigated after CPOE.

Future Considerations

The findings in this chapter were wide and varied, suggesting many potential avenues for future research. Firstly, replicating this study at other academic and community hospital systems is recommended. To further study length of stay, add patient acuity index and further explore the impact of patients being admitted via the emergency room. Additionally, it might be helpful to determine if patients had been seen prior to the emergency room visit. Attaching readmission data to the length of stay data might help us know if patients are being discharged too quickly and subsequently readmitted. The financial implications of an average decrease of 0.90 days could prove compelling.

To further study mortality, this study needs to be replicated at other institutions using the same demographic, structure, and process variables to validate or refute. Future mortality studies should include the addition of 30-day mortality rates, patient acuity measure, and more complete nursing hours worked. Sentinel events, electronic health record implementation, and the arrival of physician residents appear to have an impact on mortality. These findings are new and need to be researched to determine if changes need to be made to how institutions prepare for and implement electronic health records. Lastly, more research needs to be performed to determine if CPOE mitigates new physician resident arrival.

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CHAPTER 7

DISCUSSION

Study Summary

Millions of dollars and large amounts of time have been invested in health information technology. Much of this investment seems to be based on hypothesized or expected benefits in terms of clinical outcomes and efficiency. Research objectively assessing the impact of computerized provider order entry implementation is limited, does not represent the number of electronic health records implemented, and has shown mixed results. Studies have varied widely, in terms of patient care units, patient types, study design, and the variables examined. After a unique, isolated implementation of computerized provider order entry (CPOE) in 2009, there was the opportunity and the responsibility to assess the impact of this process change on nationally referenced outcome measures, mortality rate and length of stay. This retrospective study was performed in a 450-bed academic institution containing three different hospitals with diverse medical specialties in 22 patient care units, Coyle and Battles' (1999) adaptation of Donabedian's Structure, Process, Outcome conceptual framework (1966) guided the study; and previous studies focused on computerized provider order entry guided selection of variables (Al-Dorzi et al., 2011; Amarasingham, Plantinga, Diener-West, Gaskin, & Powe, 2009; Ammenwerth et al., 2006; Del Beccaro, Jeffries, Eisenberg, & Harry, 2006; Han et al., 2005; Keene et al., 2007; Longhurst et al., 2010; Miller &

Tucker, 2011).

This retrospective observational study used a pre-post design in which the intervention was a system-wide implementation of computerized provider order entry functionality in the electronic health record. Length of stay (measured in days) and mortality rates were the outcome variables. Covariates included patient demographics including insurance type and scheduled versus emergency admission; structure variable including patient care unit, private room, and palliative care status; and institutional processes variables including nursing care hours and the number of orders placed.

Multiple analyses using hierarchical linear modeling were performed to determine the impact of computerized provider order entry on length of stay and mortality outcome measures. Length of stay showed statistical and clinical significance for all subsets of data. On average, length of stay decreased by 0.90 days. The length of stay range decreased over time, even as the number of patient admissions increased.

Trending length of stay over time and by patient care unit led to the discovery of a "unit effect" in which findings varied by unit. Nine of 10 med/surg units had a decreased length of stay in the postimplementation phase ranging from 0.10 to 2.99 days. All 6 psychiatric units had a decrease in length of stay ranging from 0.03 to 2.87 days and the lone inpatient rehabilitation unit's length of stay increased by 0.41 days. Conversely, 4 intensive care units had an increased length of stay ranging from 1.64 to 2.46 days. Variation between patient care units length of stay decreased over the 2.5 year postimplementation phase, even as patient admissions increased. Length of stay did not experience fluctuations related to sentinel events like electronic health record implementation or new physician resident arrival. Length of stay was a more stable outcome variable evidenced by fewer and smaller fluctuations.

Mortality, consistent with some previous studies, had mixed results. Mortality statistically and clinically decreased in 4 of the 5 models. There were 1 to 4 fewer deaths per 1000 observations in the postimplementation phase. Extrapolating these rates over the postimplementation sample size of 54,470 means, depending on the model, a total of 54 to 216 patient lives were saved in the postimplementation period. Mortality was not statistically significant in the cancer specialty subset. However, the mortality rates for each patient care unit in the cancer specialty hospital still decreased. Process covariates (rapid response team activation, resuscitation activation, and palliative care status) made it difficult to interpret the clinical significance for mortality incidences. Consequently, these covariates were intentionally removed from all models so as to not overly influence the results. The mixed results suggest mortality is overly sensitive to some covariates, which seems logical given the complex interplay of factors that can cause patient mortality.

Mortality appears to be impacted by system-wide events as well as specific covariates. In the pre-implementation phase, increases in mortality were seen in the fiscal quarters preceding electronic health record implementation as well as the quarters marking new physician resident arrival. Data visualization techniques showed mortality decreased in the postcomputerized provider order entry phase corresponding to new resident arrival. This finding suggests computerized provider order mitigates the arrival of new physician residents. Future studies evaluating computerized provider order entry's impact on mortality must be sure to consider multiple covariates and system-wide events.

Trending mortality over time showed an increased number of deaths even as patient admissions increased. Although the total number increased, the mortality *rate* decreased from 1.78% to 1.75% in the postimplementation period and the range of deaths decreased over the course of the study. As expected, there was wide variation of mortality incidences and rates between the 22 patient care units. The 6 psychiatric units had one death during the entire study. Of 10 med/surg units, 8 had decreased mortality in the postimplementation phase. For all 10 medical/surgical units, mortality ranged from -4.6 to 22.7 deaths per 1000 observations. Three of 5 intensive care units had a decrease in mortality. A wider range was noted with the intensive care units, -191.4 to 45.9 incidences per 1000 visits, indicating other variables likely impact mortality.

Strengths

With the increase of electronic healthcare documentation, the opportunity to perform secondary analysis will increase in the future (Murdoch & Detsky, 2013). The findings from this study, using completeness, correctness, concordance, plausibility, and currency conceptual model (Weiskopf & Weng, 2013) and rules from Kahn, Raebel, Glanz, Riedlinger, and Steiner (2012), will assist future nurse researchers with secondary data analysis by providing real-life examples of data quality assessment processes.

In addition to the unique, isolated CPOE implementation, the strengths of this study included building upon previous studies, and expanding pre- and postimplementation phases to 2.5 years. In addition, the large data set represented diverse patient populations in 22 patient care units and contained 17 covariates. The data were examined from multiple perspectives, ranging from the entire system to the individual patient care unit, and provided a fresh and varied outlook on the outcome measures. To accommodate the multiple perspectives, simple percentages, complex statistical analyses, and data visualization strategies were performed to produce a thorough analysis of data. These analyses generated new knowledge that should guide future research.

This study is important because it examined the implementation of an expensive, time-consuming, hospital-wide electronic healthcare project relative to patient care outcomes. Many entities, ranging from patients to hospital administrators to healthcare researchers, can benefit from the findings in this study.

Limitations

Limitations for this study include restrictions on the ability to generalize to other institutions. Some of the intended covariates (body mass index and patient severity indicator) were not able to be used in the final analyses due to completeness and concordance data issues. Palliative care status, rapid response team activation, and code resuscitation activation were removed from the mortality analyses due to the unexpected impact they had on mortality indices. Because this was a retrospective pre-post design study, the analysis can only show association between CPOE and outcome variables; causality cannot be concluded from this analysis.

Future Considerations

Future studies involving CPOE need to include more and/or different covariates. Body mass index and patient severity are logical factors that could impact length of stay and mortality. Adding covariates to future studies including readmission status and 30-day mortality rates will provide more perspectives and hopefully provide insight to the sensitivity of mortality as an outcome variable. Targeted research needs to be performed at the patient care unit level to further explore the “unit effect” found in this study.

One potential impact not evaluated in this study involves the culture of the patient care unit. Items with the potential to impact the culture include training offered and received, and the willingness to help others adapt to and adopt the new technology. If nursing and ancillary staff are invested in the implementation and are willing to assist the new physician residents with finding electronic patient information, not placing orders for them, then it is possible these patient care units saw the greatest benefit. Studying the disruptive period prior to any electronic health record implementation may provide insights on how to better implement electronic health records.

Additional confounders to explore in future studies include duplicate checking, and pharmacy and lab interactions within the electronic health record. Matching patient quality of life and patient visit satisfaction scores may provide insight to length of stay fluctuations. Core measures and quality-adjusted life year measurements (QALY) may also be more available as electronic health records mature. These additional confounders could be added to strengthen future studies.

Lastly, other academic institutions need to corroborate or refute the findings related to computerized provider order entry mitigating the arrival of new physician residents. Further studying CPOE and mortality surrounding physician resident arrival may provide insights to the timing of CPOE implementation and may drive new physician resident training.

Conclusions

CPOE was statistically associated with clinically significant improvements in the system-wide outcomes. Controlling statistically for antecedent, structure, and process variables, the analysis found that after the implementation of CPOE, there was a decrease in mortality and LOS.

This study illustrated health services research by using secondary analysis, nursing knowledge, population health, and informatics knowledge to generate new knowledge. This study easily lends itself to evaluating the economic impact of an average decrease of 0.90 days. The institution is poised to rapidly perform more research with the knowledge gained from this study.

Length of stay decreased in all models, suggesting this is a relatively stable outcome indicator. However, the interplay and influence of covariates seen in the mortality models sheds light on the mixed results from previous studies. Data completeness, correctness, concordance, plausibility, and currency issues in the learning health system led to exploring the data from different viewpoints. The strong influence exerted by choice of covariates in the model as well as system-wide events indicated the need to consider the sensitivity of mortality as an outcome measure in secondary analyses related to computerized provider order entry implementation.

Future studies should include additional covariates such as body mass index, patient severity indicator, readmission data, and 30-day mortality rates to challenge the results from this study. In addition, future studies could help determine why mortality is a sensitive variable. Future studies should explore the new hypotheses generated in this study, including the “unit effect”, the potential impact of implementing electronic systems on the hospital system, and the potential impact of CPOE on new physician resident arrival and mortality rates. Lastly, more studies are needed to contribute to the body of knowledge to support or refute investments made in health information technology.

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