ASSESSING SYSTEM CONGRUENCE BY ANALYZING THE RELATIONSHIP BETWEEN EMPLOYEE AND PATIENT DRIVEN OUTPUTS

by

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A DISSERTATION

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Patients are at risk for employee driven preventable adverse events during hospital stays. These adverse events are varied and include such things as medication errors, pressure ulcers, hospital acquired infections, and falls. Preventable adverse events continue at alarming frequency despite significant academic, regulatory, and management attention to the topic over the past 14 years since the Institute of Medicine’s (IOM) *To Err is Human* report. In addition to being at risk for preventable adverse events, patients experience aspects of the health care system such as ease of access, employee attitude, skill and efficiency of staff, and perceived value. Although purporting to measure different aspects of the care experience, preventable adverse events and patient perceptions are both outputs of the health care system.

Based on the open systems theory, the organizational congruence model suggests that the non-desired outputs of the system (e.g., preventable adverse events and less-than-expected patient experiences) are due to a lack of system congruence or fit among the tasks performed, the staff performing the tasks, and the formal and informal structures. Using data from Denver Health, a large academic safety net hospital in Denver, CO, this study found that these two system outputs were significantly correlated. The study further found that using multiple regression a statistically significant predictive model could be constructed with patient perceptions of care as the DV and preventable adverse events as the IV while controlling for select explanatory variables. Finally, the study
determined that preventable adverse events fully or partially mediated select RN staffing control variables correlation with patient experience.

These findings suggest that at Denver Health good inpatient service is not divorced from good clinical quality. Management, therefore, would be well-advised to study patient experience and preventable adverse event data in combination in order to better understand important insights from one aspect of care that may help them improve another.

Keywords: preventable adverse events, patient perceptions of care, systems theory, congruence model
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CHAPTER 1

INTRODUCTION

An extensive survey of both patients and physicians revealed health professionals are fatigued and over-worked (Blendon et al., 2002). In coordinating with multiple individuals, they are inadequately communicating, misdiagnosing, and failing to follow standards (Blendon et al., 2002; Levinson & General, 2010). They are working in complex systems alongside other employees and the result is less than optimal care, as evidenced by the occurrence of preventable adverse events. Human error and system complexity are two primary reasons that preventable adverse events occur (Blendon et al., 2002). Don Berwick, former head of Centers for Medicare and Medicaid (CMS), commented: “There’s a sense that safety’s important,” but lamented “we’re [physicians, hospital administrators, etc.] too busy right now, so we can do a few things but not transformative work” (Sternberg, 2012) p. 1).

To help spur the transformative work regulatory and credentialing agencies as well as payers, patient advocates, and large employer organizations have all begun to implement quality improvement and patient safety agendas. CMS leads the effort and is working to address the problem through standardized public reporting of quality measures, economic penalties, and innovative pilots.

For most of its history, CMS, analyzed hospital quality through the efforts of experts who examined patient charts (Jencks & Wilensky, 1992). However, in the early
1990s CMS moved from chart review by experts to quantified metrics based on best practice (Jencks & Wilensky, 1992). This new approach allowed CMS to include greater numbers of hospitals and focus on large sample averages rather than a few non-representative outliers (Jencks & Wilensky, 1992). The first large scale project by CMS using these new data was the Cooperative Cardiovascular Project (CCP) (Marciniak et al., 1998). The project was started on a limited basis in four states in the early 1990s and was ultimately expanded nationwide. The project focused on acute myocardial infarction or AMI. Marciniak et al. (1998) showed broad success in the four pilot states. Process outcomes related to administration of beta blockers and aspirin on arrival showed significant increases in compliance, while the outcome of mortality also showed significant improvement (Marciniak et al., 1998). From these early efforts CMS has expanded its quality measurement efforts to include many other conditions.

In addition to defining and collecting quality metrics, CMS has made hospital quality and patient perception data available to the public through its Hospital Compare website ("Hospital Compare," 2013) in order to encourage patients to make informed buying decisions. CMS is also tying Medicare reimbursement to quality through its value-based purchasing program wherein reimbursements are withheld and earned back by providers that meet pre-defined quality outcomes (VanLare & Conway, 2012). These value-based purchasing adjustments began at 1% in 2013 and will increase to 2% by 2017 (McKinney, 2013).

Beginning in 2015, CMS will begin penalizing providers 1% of total payments for a variety of hospital acquired conditions (McKinney, 2013). This is the third and final value-based purchasing program authorized under the Affordable Care Act (McKinney,
In total, there are $1 billion in Medicare payments at risk beginning in 2013, with the amount doubling by 2017 (Merlino & Raman, 2013). CMS is also funding pilots to improve quality and reduce preventable adverse events. For example, CMS recently provided $5 million in funding to a consortium of Ohio Children’s Hospitals to study preventable errors (Brilli et al., 2010).

CMS is not the only organization attempting to improve quality and reduce preventable adverse events. The Agency for Healthcare Research and Quality (AHRQ), a federal agency of Health and Human Services, evaluates and reports on clinical quality in an effort to improve quality and to apply pressure to providers to reduce preventable adverse events (Berenson, Pronovost, & Krumholz, 2013). For example, in the January 23, 2014 edition of *The New England Journal of Medicine*, Wang et al. (2014) published a seven-year study of adverse events across four conditions. This research was funded by AHRQ. Similarly, The Joint Commission (TJC), a private healthcare credentialing organization, is focusing efforts on improving patient safety and reducing unnecessary harm. TJC has established Patient Safety Goals that include preventing infections, administering medications properly, identifying patients correctly, and communicating with patients in an appropriate and timely manner.

Employer advocacy groups and large employers have also begun to take action to improve quality patient outcomes. The Leapfrog Group (“The Leapfrog Group,” 2013) was founded with the goal of pooling the purchasing power of employers to affect improvements in quality from providers. It has become a prominent employer healthcare advocate and notes on its website the organization’s mission is “to trigger giant leaps forward in the safety, quality and affordability of health care” (para 1). In 2012, the
Leapfrog Group published its first Hospital Safety Score. The Hospital Safety Score assigns a letter grade to each hospital on how well they are keeping patients safe. The Leapfrog Group represents 22 large employers such as Boeing and 33 Organizations of Purchasers such as the Dallas-Fort Worth Business Group on Health which in total cover 34 million Americans and $62 billion in healthcare expenditures ("The Leapfrog Group," 2013). Independent of such groups as Leapfrog, large employers have also started directly steering business to healthcare providers that offer high quality patient service and are willing to provide transparent pricing and low cost. For example, citing quality and cost, Lowes, a national home improvement company, negotiated bundled payments two years ago with the Cleveland Clinic on open heart care for its employees and their families (Glen, 2012).

A number of organizations are working directly with the healthcare professionals to advance patient safety goals. For example, the National Association of Healthcare Quality (NAHQ) and Institute of Healthcare Improvement (IHI) work with providers, quality professionals, and provider organizations to improve patient safety. NAHQ and its 40 state affiliates have attempted to raise public awareness and promote professional competency by supporting the quality professionals within the healthcare industry with education, tools, and networking opportunities ("National Association for Healthcare Quality," 2013). Through its *Triple Aim* program, IHI is working with providers to improve the quality of care for large populations, provide a better individual patient experience, and lower per capita healthcare costs ("The IHI Triple Aim Initiative," 2013).

A number of for-profit organizations, such as Healthgrades and *US News and World Report*, synthesize publicly available information and publish quality and safety
rankings and other consumer guides. In February of 2014, Healthgrades published its 100 Best Hospitals™. According to the Healthgrade website the hospitals represented on this list have a risk-adjusted mortality that is 24.53% lower than all the other hospitals ("Healthgrades," 2014). Similarly, US News and World Report published its “Best Hospitals Rankings” based on surveying 10,000 specialists and analyzing data from 5,000 hospitals ("US News Best Hospitals 2013 - 2014," 2014). These data are reported by clinical specialty. In the latest rankings, only 147 institutions were ranked as a top hospital across at least one of the 16 measured adult specialties ("US News Best Hospitals 2013 - 2014," 2014). It is worth noting that only 18 of the 147 institutions made the US News and World Report honor roll requiring top performance in at least 6 specialties ("US News Best Hospitals 2013 - 2014," 2014).

Finally, in addition to imposition of new measurement, regulations, pilot programs, advocacy, rankings, economic incentives and penalties, healthcare providers themselves are interested in distinguishing their organizations and seeking a competitive advantage in the marketplace by touting high quality. The Malcolm Baldrige National Quality Improvement Award was established in 1987 by an act of Congress to improve the competitiveness of U.S. business. The act was modified in 1999 to allow healthcare organizations to participate ("Baldrige Performance Excellence Program," 2013). Since 2002, there have been 16 Baldrige healthcare winners with no less than one given each year.

In addition to industry efforts to improve quality, significant efforts are being made to improve the patient care experience and thereby enhance patient perceptions of the care they receive. In fact, one of the three main tenets of IHI’s Triple Aim is
dedicated to improving the patient experience. To measure patient perceptions of care on a national basis, survey instruments are used. The most prevalent survey tool is the suite of Consumer Assessment of Healthcare Providers and Systems (CAHPS) surveys developed by AHRQ beginning in 2002 and subsequently endorsed in 2005 by National Quality Forum (NQF), a quasi-public organization that evaluates new measurements on behalf of its many stakeholders (Berenson et al., 2013). Appendix A identifies the list of the various types of CAHPS surveys.

The CAHPS survey tool that is used to assess patient perceptions of care related to inpatient hospital stays is referred to as Hospital Consumer Assessment of Healthcare Providers and Systems or HCAHPS. HCAHPS is a patient experience survey which is administered nationally with a standard set of questions. CMS began requiring the administration of the HCAHPS survey in 2006; CMS began publicly reporting the data on its Hospital Compare website in 2008 ("Surveys and Guidance," 2012). This survey provides transparency of results and includes patient perceptions related to multiple categories as shown in Table 1.

Table 1

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<th>Categories</th>
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<tr>
<td>Nurse Communication</td>
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<td>Doctor Communication</td>
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<tr>
<td>Explanation of Medicines</td>
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<td>Timely Help from Hospital Staff</td>
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<td>Information About Recovery</td>
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<td>Pain Control</td>
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<td>Cleanliness</td>
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<td>Quiet at Night</td>
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<td>Patients’ Rating of Hospital</td>
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<td>Would Recommend Hospital</td>
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Like clinical quality outcomes, patient experience is a national priority, and CMS is tying performance to pay. In 2014, 30% of the value-based purchasing formula used to determine bonuses and penalties to providers will be based on the Patient Experience of Care as measured by HCAHPS ("CAHPS hospital survey," 2013).

Efforts to improve quality and the patient perception of care are not without detractors. Ryan, Nallamothu, and Dimick (2012) concluded that the public availability of the CMS Hospital Compare Website and the requirement that hospitals report selective quality data has led to no reductions in mortality due to heart attack or pneumonia and only modest declines in mortality related to heart failure. Some industry leaders suggest that the hospital centric business model based on volume is the problem ("Inventing the future of healthcare," 2013) and transformative ideas are needed (Buescher & Vigerie, 2014). These reports suggest that an incremental approach to quality improvement may not be sufficient.

Despite the concerns with these data, programs, and current business models, healthcare regulators, payers, and competitor organizations are using these indicators to set policies, restrict payments, and create competitive advantages. All of these examples suggest that poor quality health outcomes are becoming increasingly harder to hide. Demands for public reporting of quality and pay for performance are rising (Berenson et al., 2013) not declining. As such, healthcare managers must diligently work to provide high quality services that meet patient expectations.
Research Question

Reducing preventable adverse patient events and improving patient perceptions of their experiences are undeniably high priorities for healthcare leaders. However, large hospitals have many inpatient units with patients of all ages and conditions. These units are staffed by unit leaders, nurses, and other allied health professionals with varying skill levels and experience. In short, inpatient care units are complex environments or sub-systems where preventable adverse events and less-than-expected patient experiences could occur at any time.

The purpose of this study was to examine these complex inpatient care units to determine if system performance could be better understood and potentially improved through a more in-depth understanding of the system’s inputs, transformations and outputs. Since outputs are products of the system, they can be used to assess system performance. Hospital managers can use system outputs as part of a feedback loop to improve reliability and prioritize and sustain needed improvements. Therefore, the following initial question guided this investigation. Can management glean new insights into improving patient care outcomes by connecting the dots across disparate clinical quality and patient experience data? To that end:

Are the documented preventable adverse events made by employees correlated with patient perceptions of care at the inpatient unit level?

Are there other factors that contribute to the correlation that can be defined, quantified and controlled in order to better understand the correlation between preventable adverse events and patient perceptions of care?
What can be learned by studying the other factors’ effect on preventable adverse events and patient perceptions of care?

It is important to note that the research questions pertain to correlations at the inpatient unit level, not the individual patient level which tend to be more concerned with health status, recovery and health maintenance (Porter & Lee, 2013).

It is also important to note that the research questions do not aim to answer whether patient’s perceptions of care measure clinical quality. Rather the question looks at whether the patient’s perception of the care is consistent with the quality of the care (Press, 2014). If a correlation exists between preventable adverse events and patient perceptions of care at the inpatient unit, then improvement resources could be allocated to the areas with the highest needs. Since hospital quality improvement resources are limited, the ability to expend assets on the areas with the greatest needs would be of value to hospital administrators. These insights would be especially useful if they were readily available and timely for decision-makers. Currently, most hospitals track the following rich data sources related to inpatient unit performance:

**EMPLOYEE DRIVEN**

1. Preventable adverse event reporting

**PATIENT DRIVEN**

2. Patient perception survey results
3. Patient complaints

These data sources are available at the inpatient unit level. In addition, each data source provides direct feedback regarding how the inpatient unit is performing. The first category of data, preventable adverse events, represents unwanted employee-driven
system outputs. Automated rules-based preventable adverse event databases can provide the volume of preventable adverse events while simultaneously eliminating any reporting bias that can be present in voluntary reporting systems.

The second category of data is patient driven system outputs. Patient perception survey results reflect input from a random yet statistically significant sample of patients. Results are tabulated by question and by discharge unit and reported to hospital leaders for analysis. These data represent the voice of the patient. Patients are able to comment directly on attributes that impacted their expectations of the care they received (e.g., long waits, staff rudeness, disjointed processes, incompetence of staff). Similarly, patient complaints are typically logged by date and by unit as they occur and coded based on the nature of the complaint. These logs document specific instances in which patients expressed dissatisfaction with some aspect of their hospital experience.

Previous researchers have suggested that preventable adverse events are due in large part to human error or complex systems (Blendon et al., 2002; Sandars & Esmail, 2003). Therefore, patient perception data, based on firsthand exposure to the same complex systems and the individuals who work in these systems, should be correlated. While hospitals currently use preventable adverse event data and patient perception data to make improvements, this current research considered whether or not preventable adverse event data could be used in conjunction with patient perception data to provide a stronger predictor of inpatient unit performance.
Practical Applicability

If a correlation exists between preventable adverse events and patient perceptions of the healthcare system at the inpatient unit level, then healthcare managers will have a more exact approach with which to focus performance improvement initiatives. Armed with this information, managers can better align scarce improvement resources to the areas with the greatest needs for improvement. Further, to the extent this information can be provided on a timelier basis, prioritized interventions can be initiated sooner. Insights gleaned from timely measurement of one aspect of care could be used to alert management of potential issues in another aspect of care.

The ability to interpret and act on system output data is an important role of managers. It is incumbent upon the manager to ensure that human resources, technology, and the relationships that comprise the system properly adapt to the ever changing environment. If the system is performing poorly, the manager must modify the system based on informed feedback. The findings from this research could help managers draw inferences from disparate data sets in order to improve outputs such as improved patient safety and enhanced patient experiences.
CHAPTER 2
LITERATURE REVIEW

Healthcare System Outputs

Assessment of healthcare system performance has both a technical component, where outcomes are measured against agreed upon standards, and a subjective component, where outcomes are measured against patient expectations (Coulter, 1991). A great deal of research has been conducted in terms of the technical elements of care (e.g., preventable adverse events) as well as the subjective elements of care (e.g., patient perceptions of care).

*Preventable adverse events*

Patients are at risk for preventable adverse events in hospitals (Brennan et al., 1991). These preventable adverse events take several forms. For example, patients get infections, they are given the wrong medicine or the right medicine at the wrong time or in the wrong dose, they acquire pressure ulcers, and they are at risk of falling. As regulatory reporting requirements become stricter, these preventable errors become more public.

In 2010, the Department of Health and Human Services Office of the Inspector General (DHHS OIG) reported that during a one month period 134,000 of the one million Medicare beneficiaries admitted to a hospital suffered from an adverse preventable event (Levinson & General, 2010). The report estimated that the monthly cost to CMS for these preventable events was $324 million. The report identified 36 separate preventable events and divided them into four categories, as shown in Table 2.
In the same year as the DHHS OIG report, a five-year longitudinal study was published in the New England Journal of Medicine (NEJM) that examined preventable errors in 10 North Carolina hospitals (Landrigan et al., 2010). The goal of the study was to determine if preventable errors declined as time elapsed from the years 2002 to 2007. That is to say, were hospitals providing better quality over time given the increased attention to the topic? The authors selected a stratified random sample of 100 admissions per quarter. Using the Institute of Medicine’s (IOM) global trigger tool, teams of internal and external nurse reviewers evaluated each admission. If an adverse event was suspected the chart was reviewed by a team of two physicians. Reviewers identified 25 patient harms per 100 admissions for a rate of 25% with a 95% confidence interval. The authors concluded that there was no statistically significant decline in preventable errors over the course of the study period.

An interesting footnote to Landrigan’s 2010 research is a 47-year-old study by McLamb and Huntley (1967). Like Landrigan, the authors studied adverse events (or “episodes”) in a North Carolina Hospital. Despite the span in years and advancements in

<table>
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<tr>
<td>Events related to medication</td>
<td>31%</td>
</tr>
<tr>
<td>Events related to patient care</td>
<td>28%</td>
</tr>
<tr>
<td>Events related to surgery</td>
<td>26%</td>
</tr>
<tr>
<td>Events related to infection</td>
<td>15%</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
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medicine, the two studies produced similar results with the McLamb and Huntley (1967) study showing a slightly better 20 patient harms per 100 admissions.

In a study similar to Landrigan and McLamb and Huntley, Longo, Hewett, Ge, and Schubert (2005) reached the same conclusion. According to these authors, despite the attention to preventing unnecessary injury to patients, “hospital patient safety systems are not close to meeting current IOM recommendations” (p. 2858).

As noted in the landmark study by the IOM, To Err is Human, as many as 98,000 Americans die each year due to medical errors with over half of these deaths avoidable (Kohn, Corrigan, & Donaldson, 2000). Referring to the IOM study, Paul Levy, former CEO of Beth Israel Hospital (Sternberg, 2012), stated, “I don’t think that crashing a 727 jet every day and killing everybody on board is a good standard of care in U.S. hospitals. If that happened in aviation they would shut the airlines down” (p. 1).

One area of concern is hospital acquired infections. The Centers for Disease Control and Prevention (CDC) estimates that hospital acquired infections affect over two million people each year in the United States (Gaynes et al., 2001). Through its Healthcare Quality Promotion Division, the CDC manages the National Healthcare Safety Network (NHSN) (Hidron et al., 2008). NHSN consolidates information from what were previously three separate systems: National Nosocomial Infections Surveillance system, the Dialysis Surveillance Network, and the National Surveillance System for Healthcare Workers (Hidron et al., 2008). In reviewing data from a NHSN report covering 463 hospitals that had reported at least one hospital acquired infection, Hidron et al. reported the following incidents of infections among the four primary type of device and procedure related infections: 28,502 infections were reported to NHSN
from 463 separate hospitals from January 2006 until October 2007. Central line associated blood stream infections (CLABSI) accounted for 10,064 (35.3%); catheter associated urinary tract infections (CAUTI) 8,579 (30.1%); ventilator associated pneumonia (VAP) 4,524 (15.9%); and surgical site infections (SSI) 5,291 (18.6%) (Hidron et al., 2008).

Another category of preventable adverse events is medication errors. Despite efforts by academic researchers and health professionals, medication errors in hospitals are still prevalent and growing in number (Harrington, 2005). One widely cited study evaluated adverse drug events in two large tertiary hospitals across 11 medical/surgical inpatient units for all patient admissions over a six month period. According to Leape et al. (1995), 334 medication errors occurred during the time period resulting in 264 preventable or potential preventable adverse drug events. In another study, researchers looked at 36 hospitals and skilled nursing facilities in Georgia and Colorado and reported 19% of the doses were in error with the largest categories of error being wrong time (43%), missed (30%), incorrect dose (17%), and incorrect medication (4%) (Barker, Flynn, Pepper, Bates, & Mikeal, 2002).

Like hospital acquired infections and medication errors, pressure ulcers have also become problematic. In one study of 3,233 hospitalized patients over 65 years of age, none of the patients had pressure ulcers upon admission. However, approximately 200 patients (6.2%) acquired pressure ulcers while in the hospital (Baumgarten et al., 2006). Pressures ulcers strike the elderly and can occur within hours if the patient is not turned properly. In addition to age, Baumgarten and colleagues (2006) noted other significant characteristics attributable to increased incidence of pressure ulcers to include “male
gender, dry skin, urinary and fecal incontinence, difficulty turning in bed, nursing home residence prior to admission, recent hospitalization and poor nutritional status” (p. 749). Taken together, these characteristics represent a sizable at-risk patient population.

Falls are considered to be one of the most common patient accidents (Sutton, Standen, & Wallace, 1993). It is estimated that 30% of falls result in injury (Dunton, Gajewski, Taunton, & Moore, 2004; Hitcho et al., 2004) and occur at a rate of 2.3 to 7 falls per 1,000 patient days (Hitcho et al., 2004), with a separate study calculating the mean at 3.73 days (Dunton et al., 2004). Falls with injuries can prolong the hospital stay by 12.3 days and add $4,200 in extra charges (Bates, Pruess, Souney, & Platt, 1995).

Patient Perceptions of Care

Hospital acquired infections, medication errors, pressure ulcers, and falls are all examples of undesired outcomes of the hospital system. They represent outcomes that undermine technical performance standards. Patient perceptions of care are another output of the hospital system. When patients are admitted to the hospital they enter into a healthcare system. Patients are encouraged to provide feedback of their experiences to healthcare providers and managers in a variety of ways including: communication with patient advocates, suggestion boxes, committees, regulatory avenues, focus groups, public venues, and formal and informal surveys (Jones, Leneman, & Maclean, 1987). However, this was not always the case. McIver (1991) suggested that management’s increasing interest in formally measuring patient satisfaction with care can be traced to the early 1980s and has its origins in the rise of consumerism (i.e., the need to protect and educate consumers regarding the products and services they purchase).
One form of eliciting patient feedback is through a formal survey process. Early patient perception surveys were developed primarily by managers; these surveys assessed physical environment and hoteling items, such as the quality of the food (Fitzpatrick, 1991). However, Fitzpatrick (1991) argued that there were three more meaningful reasons to survey patients:

1. Patient perceptions are outcomes of the healthcare system and as such provide feedback on such things as the patient’s likelihood to follow suggested treatments or switch providers;

2. Patient perceptions are useful in assessing effective communication between patients and providers;

3. Patient perceptions give managers insights into how best to organize healthcare systems, e.g., hours of operation.

Fitzpatrick recognized patient perceptions as outputs of a system and viewed surveys as a means to measure these perceptions. There is, however, an academic debate regarding the effectiveness of patient perception surveys. Sitzia and Wood (1997) noted that one weakness in the evaluation of patient perceptions is that the measurement tools (i.e., the surveys) preceded the theoretical and conceptual research, thereby calling into question the interpretation of results. Other criticisms include cost to implement and subject to bias based on large swings in response rates (Berenson et al., 2013).

Despite these shortcomings, patient perception surveys are pervasive. In the U.S., there are numerous private patient perception survey firms. In April 2012, Modern Healthcare listed seven patient satisfaction measurement firms with over 2,000 annual consulting engagements ("Largest patient satisfaction measurement firms," 2012). Each
of these market leading firms has a proprietary product that it markets directly to the healthcare industry. Appendix B lists the firms from the Modern Healthcare list. However, it was not until 2005 that the CAHPS survey, a national standard for assessing patient perceptions, was introduced ("CAHPS hospital survey," 2013). CAHPS was designed by AHRQ, and has subsequently been reviewed and endorsed by NQF and adopted by CMS.

With CAHPS, CMS intended to address shortcomings associated with multiple vendors providing private patient perception surveys. Specifically, CMS wanted to ensure comparable consumer insights across hospitals. In addition, through public reporting of results, CMS intended to create a strong incentive for hospitals to improve care. Finally, CMS needed patient perception data so that it could better link public financing of healthcare with results ("CAHPS hospital survey," 2013).

Patient complaints are another form of measuring patient perceptions. Like perception surveys, the formal complaint process provides patients an avenue to provide feedback (Jones et al., 1987). Schwartz and Overton (1992) acknowledged the importance of patient perceptions in the form of complaints, and challenged the assumption that patient feedback is of little value because it is not rooted in medical science (Schwartz & Overton, 1992). A study at Vanderbilt University examined seven years’ worth of patient complaints and looked for patterns across operational units and by category of complaints (Pichert et al., 1999). The overriding conclusion of the study was that by globally studying complaints and looking for patterns, rather than just addressing each individual complaint, managers would enhance their ability to prevent future complaints (Pichert et al., 1999).
Applicable Research Linking Preventable Adverse Events and Patient Perceptions

There are numerous studies that attempt to determine the underlying predictors of preventable adverse events. The richest areas of current research are the studies attempting to determine the relationship between clinical staffing and patient outcomes. Unruh (2008), a professor at the University of Central Florida, documented 21 relevant studies from 2002–2006 aimed at understanding this relationship. Additionally, researchers are studying preventable adverse events to understand the costs (Thomas et al., 1998), examining clinical and patient characteristics to better predict and ultimately reduce occurrences (Brennan et al., 1991), and exploring how best to measure and report the data (Berenson et al., 2013).

Similarly, there are several studies attempting to determine the underlying predictors of patient experience. One such study looked at characteristics of the patient (e.g., age, gender, and education) to see if there were correlations with levels of satisfaction (Quintana et al., 2006). The authors discovered that indeed some patient satisfaction could be tied to specific patient characteristics such as age, gender, education, and marital status when analyzed with categories of satisfaction such as visiting, nursing care, information, human care, comfort, intimacy, and cleanliness. Other studies have examined whether characteristics of the nursing staff predicted patient satisfaction at a given point in time (Larrabee et al., 2004) or over several years (Seago, Williamson, & Atwood, 2006).

Few researchers, however, have investigated these two areas simultaneously. Cleary and McNeil (1988) noted, “there have been few studies of the extent to which the medical outcome of care is related to patient satisfaction” (p. 30). Vouri (1991)
demonstrated that there was no evidence in the literature where measuring patient satisfaction improved quality outcomes, yet the author argued for continuing to measure patient satisfaction as a means to engage the patient as a consumer and to highlight patient expectations as a quality indicator. O’Connor and Shewchuk (2003) stipulated that a satisfied patient is more desirable than a dissatisfied patient. Like Vouri, however, the authors found no strong evidence in the literature to suggest that improving patient satisfaction had a measurable impact on clinical quality outcomes.

Although the literature lacks research on a causal relationship, there are a few researchers who have looked for a correlation between quality outcomes and patient perceptions. Kane, Maciejewski, and Finch (1997) studied over 2,000 laparoscopic cholecystectomy patients and found a significant relationship between satisfaction and quality outcomes. However, the researchers observed that only slight variations in satisfaction levels could be attributed to the outcomes (Kane et al., 1997).

Covinsky et al. (1998) identified a positive relationship between patient health status at the beginning of the hospital stay and their level of satisfaction. This relationship also held when examining health status at discharge. Changes in health status during the hospital stay were only correlated with patient satisfaction to the extent that changes were reflected in discharge health status (Covinsky et al., 1998). Based on these findings, the authors suggested that changes in health and patient satisfaction were actually measuring two different domains of outcomes (Covinsky et al., 1998). Press (Press, 2014), co-founder of Press Ganey [national U.S. patient satisfaction survey firm] and professor emeritus at Notre Dame argued that patient evaluations of the care they received is not confined to the technical aspects of their care but “includes empathy and behaviors that
address the emotional, informational, social, cultural and economic issues that accompany sickness and its treatment” (p. 40). Finally, although not extensive, some research has been conducted on the correlation of patient care and patient complaints. One study found that unsolicited patient complaints related to quality of care were found to be associated with increased medical malpractice risk (Hickson et al., 2002).

In summary, this current study attempted to build upon the current body of research literature. The focus of the study was not to establish a causal relationship at the patient level between preventable adverse events and patient perceptions of care to determine if one accurately measured the other, but rather to determine if at the sub-system inpatient unit level the two separate output measures were correlated despite measuring different attributes, i.e., the technical quality and experience quality.

Relevant Theory

As noted in the previous section, preventable adverse events in healthcare are not uncommon. Health professionals are fatigued and over-worked. In coordinating with multiple individuals, clinical staff members are inadequately communicating, misdiagnosing, and failing to follow standards (Blendon et al., 2002; Rogers, Hwang, Scott, Aiken, & Dinges, 2004). Individuals are working in complex systems alongside other health professionals, and the results are less than optimal care. Albeit unintended, each occurrence of a preventable adverse event and hospital stay that falls short of patient expectations is an undesired output of the care delivery system. Therefore, to better understand system performance it is necessary to better understand systems. This
understanding is aided by the use of theory and conceptual models, such as the open systems theory.

Open Systems Theory

Rooted in biology, open systems theory was postulated by Von Bertalanffy (1950) to appeal to a wide range of scientists who were interested in the study of systems. Specifically, open systems theory was focused on the interactions of the various components that comprise the system (Von Bertalanffy, 1950). In their seminal work, *The Social Psychology of Organizations*, Katz and Kahn (1978) suggested that open systems theory could help close two gaps, namely, a gap in understanding the behavior and interactions of people in organizations and a new way to define organizations beyond the historical definitions of bureaucratic, public administrative, and scientific, as articulated by Weber, Gulick, and Taylor, respectively.

Katz and Kahn (1978) defined open systems as the cycle of taking input from the environment, transforming the input, and exporting it back into the environment. According to the authors, the same general characteristics of systems hold true for organizations as well. All open systems also share other characteristics including: (a) negative entropy, the idea that open systems must take in more inputs than the system exports; (b) feedback, the means by which the system self corrects; (c) equifinality, the ability to achieve a similar output in several different ways; (d) hierarchy, the existence of lower order subsystems; and (e) internal elaboration, the concept that systems move to higher levels of organization (Kast & Rosenzweig, 1972; Katz & Kahn, 1978; Nadler & Tushman, 1980).
Despite the promise of this theory to help researchers and managers understand the dynamics associated with system components, both Katz and Kahn and Kast and Rosenzweig recognized that the field of systems research was not fully developed. In particular, Kast and Rosenzweig suggested that the field continues to use open systems theory as a foundation to explore second-order systems where the research can be more concrete and the studied characteristics and relationships can be more specific (Kast & Rosenzweig, 1972). Consistent with this challenge, Nadler and Tushman developed the organization congruence model.

**Congruence Model**

General systems theory provides insights into organizations as open systems. However, as Kast and Rosenzweig noted, additional conceptual models are needed to provide the framework for a better understanding of system performance. One such model is the congruence model of organizational behavior (or congruence model) developed by Nadler and Tushman (1980). The congruence model builds on general and open systems theory and provides a framework for understanding an organization’s output in light of the organization’s inputs and transformational processes.

Where open system theory is more general, the congruence model is more specific, allowing for interpretation at the sub-system level. As Nadler and Tushman noted, individuals often describe their organizations through static, interrelated, and hierarchical boxes. This viewpoint, however, is limiting and thereby forecloses the option of organizations as dynamic open systems (Katz & Kahn, 1978).
The organizational congruence model indicates that organizations must be consistently managed and structured to be effective. According to the authors, inconsistent management practices or misaligned structures invariably lead to less than desired results (Nadler & Tushman, 1980). The key, therefore, is “fit.” Departments must interact effectively to achieve results. They must work together as an interdependent system rather than a system of independent subparts. When organizational units “fit” and work well together the organization is congruent and functions as intended. However, the inverse is also true (Nadler & Tushman, 1980).

As proposed by Kast and Rosenzweig, Nadler and Tushman divided organizations into component parts. Nadler and Tushman noted that organizations were comprised of tasks, individuals, and formal and informal organizational structures. Tasks describe the work that needs to be performed, individuals are the people who perform the tasks, and structure describes how the work is organized both formally and informally. All four of these organizational components must fit together in order for the organization to be effective. Individuals must be congruent with the tasks, tasks must be congruent with the formal structure, and so on. The details of the congruence model components as described by Nadler and Tushman can be found in Figure 1.
The interplay of components in Figure 1 demonstrates the ways in which various elements can affect organizational performance. For example, in the case of the acute care hospitals, inputs include patient expectations, regulatory requirements, staff, technology, the history of the hospital, and current priorities of hospital management. The transformation includes all of the complex tasks that must be performed by the staff in

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1 Adapted from Organizational Dynamics, Autumn 1980, A model for diagnosing organizational behavior, pp. 35 – 51, Copyright (1980), with permission from Elsevier.
order to provide acute inpatient care. Given the highly specialized tasks that must be performed, there is a need for highly specialized health providers including: physicians, nurses, technicians, therapists, and many more. Highly specialized work tasks are organized formally in nursing units and informally by profession. Outputs, therefore, include the care patients received and the performance of that delivery of care. A visual depiction of the congruence model can be found in Figure 2.

![Figure 2: Congruence model](image)

The congruence model helps bring understanding to real world applications. For example, the model suggests that for the system to achieve its intended outputs there must be a good fit between the key areas of people, tasks, and formal and informal structures (i.e., transformation). Clearly, if the individuals do not possess the necessary

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skills, the work is poorly designed, and the organization of the work is sub-optimal then
the desired outputs of the system cannot be achieved. In short, desired outputs require fit
or congruence between the inputs and transformation. The task of ensuring congruence is
the responsibility of hospital managers. To ensure that all of the component parts of the
system are working in concert, managers can use the feedback loop in the model to assess
the system. Based on the feedback, managers can adapt the system to improve the
outputs.

**Systems Theory and Congruence Model in Practice in Healthcare Settings**

The research literature is replete with examples in which systems theory was
applied in a healthcare setting to describe the environment. In IOM’s *Cross the Quality
Chasm*, Plsek (2001) described systems theory as a means to understand the
interconnectedness of the United States healthcare system at the macro and micro levels.
The macro level was comprised of hospitals, insurance companies, government payers,
pharmaceuticals, and more, while the micro level included a physician clinic with
doctors, nurses, and other staff.

Systems theory has also been applied in research related to health information
technology (IT). Lee and Xia (2005) referred to systems theory to explain how the
adoption of an information system is both a technical process and a social process.
Berwick (1998) proposed that systems theory could “help physicians participate more
effectively in the redesign of the health care system” (p. 289). While not mentioning
systems theory by name, Donabedian (1966) contributed to systems theory by developing
a framework for assessing quality. As demonstrated in Figure 3, this framework
expanded the transformation step of systems theory to include process and structure.

More recently, Anderson, a recent DSc graduate at the University of Alabama at Birmingham (UAB), applied systems theory to a study of oral health disparities among children in Milwaukee, WI (Anderson, 2012). These citations represent a small sample of how systems theory and the congruence model have been used to address real world concerns in the healthcare industry.

Figure 3. Donabedian’s model of patient safety, as modified by Coyle & Battles.³

CHAPTER 3

RESEARCH METHODOLOGY

Study Purpose and Research Questions

The purpose of the study was to provide health care managers with additional insights regarding the congruence and ultimately the performance of hospital sub-systems, i.e., inpatient units. These inpatient systems take in inputs such as environment expectations (e.g., regulations and patient demands), resources (e.g., staff, technology, capital, and information), organizational history and strategy, and then transform inputs through tasks, individuals’ skills, and formal and informal structures. Finally, inpatient systems produce outputs which include the quality of the product and the fulfillment of the patient’s expectations (Nadler & Tushman, 1980).

Preventable adverse events are an output of the inpatient unit system. Preventable adverse events are mistakes made by employees and represent an undesired system result. Similarly, patient perceptions of care are an output of the system and an indication of whether the demands of the patient have been met. The absence of preventable adverse events and the existence of met patient expectations are two indications of a system in congruence.

Preventable adverse events and patient perceptions measure outputs from the same system yet in large part they measure different things (Covinsky et al., 1998). Preventable adverse events represent the technical delivery of care in which patient perceptions of care are a subjective measure. Preventable adverse events are categorized under medications, patient care, surgery, and infections (Levinson & General, 2010). Patient perceptions, on the other hand, tend to evaluate more subjective areas such as
empathy and staff behavior (Press, 2014). The HCAHPS survey tool measures nurse and doctor communication, explanation of medication, timely help from hospital staff, information about recovery, pain control, cleanliness, noise levels, and overall patient recommendations ("CAHPS hospital survey," 2013). Similarly, complaints are filed by patients for a variety of reasons when expectations are not met. The goal of the study was to assess at the inpatient unit level whether these system outputs arrived at the same conclusion regarding system congruence despite measuring different aspects of the system. Specifically, the study attempted to address whether the volume of preventable adverse patient events was correlated with patient perceptions of the care they received?

Research questions are summarized below:

**Question 1**: Are the documented preventable adverse events made by employees correlated with patient perceptions of care at the inpatient unit level?

**Question 2**: If yes, are there other factors that contribute to the correlation that can be defined, quantified and controlled in order to better understand the correlation between preventable adverse events and patient perceptions of care?

*Sub-Question 2.1*: Is the predictive value of the model improved by adding relevant control variables from categories such as patient acuity, unit churn, patient time on the unit, and clinical staffing?

*Sub-Question 2.2*: Do preventable adverse events remain correlated with patient perceptions of care after adding relevant control variables described in 2.1?

**Question 3**: What can be learned by studying the other factors’ effect on preventable adverse events and patient perceptions of care?
Sub-Question 3.1: To what extent is the correlation between clinical staffing variables and patient perceptions of care mediated by preventable adverse events?

The goal of research question one was to understand the relationship between preventable adverse events (i.e., the IV of interest) and patient perceptions of care (i.e., the DV). This was a straightforward analysis of correlation between two continuous variables.

Question two expanded upon the answer to research question one. If a correlation existed, could the predictive model be improved through the introduction of relevant control variables and did the correlation between the IV of interest and the DV remain?

The third research question attempted to better understand the results of the first two research questions. In particular, it determined if the correlation between the DV and the CVs pertaining to RN staffing were partially mediated by preventable adverse events. In other words, did RN staffing help explain preventable adverse events which in turn helped to explain patient perceptions of care? Staffing variables were singled out for this analysis for two reasons: first because of the strong support in the literature regarding staffing’s effect on both the technical and subjective aspects of patient care (Unruh, 2008) and second because management has more control over staffing than the other CVs. For partial mediation to be present, four conditions must have been met:

1. Significant relationship between an independent variable (X) and the DV (Y).
2. Significant relationship between X and the potential mediator (Z).
3. X still predicts Y after controlling for Z.
4. The relationship between X and Y is reduced when Z is in the equation.

(Tabachnick & Fidell, 2013).

Open systems theory and the congruence model provided a conceptual framework with which to analyze these research questions. As previously noted, the congruence model (Figure 1 and Figure 2) is comprised of inputs, transformation, and outputs. Inputs include environmental factors (e.g., customer demands, regulatory barriers, and market opportunities); resources (e.g., employees, technology, capital, and information); organizational history; and strategy. The transformation process organizes and aligns tasks, personnel, and informal and formal structures. Outputs of the model include products and organizational performance.

In the context of this specific study, system inputs included employees and patients. Employees are a necessary resource to produce the desired outputs of the system while patients bring expectations and demands. Employees work within the structures (both formal and informal); perform tasks in order to meet patient expectations; and produce a product that meets, exceeds, or falls short of standards. Patients, on the other hand, move through the system. They experience the structures (both formal and informal), the personnel, and the tasks performed on their behalf. Figure 4 illustrates how employees and patients move through the same system.
**Research Hypotheses**

The congruence model suggests that an organization that is not achieving its desired organizational performance lacks fit, or congruence, between the tasks that it performs, the people who perform the tasks, and the formal and informal structures of the organization and business model. The lack of organizational congruence leads to a dysfunctional system which leads to undesired system outputs. In the acute care hospital setting, the prevalence of preventable adverse events would suggest a lack of organizational congruence. Similarly, poor patient perceptions would indicate an undesired system output and therefore a lack of congruence. *Given that preventable adverse events and patient perceptions of care are outputs from the same system, it may be expected that these two outputs are correlated with one another.* For example, a high incidence of preventable adverse events would be correlated with negative perceptions of care (see Figure 5).

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**Figure 4. System congruence.**

<table>
<thead>
<tr>
<th>Inputs</th>
<th>Transformation</th>
<th>Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Patients</strong></td>
<td>Experience the System</td>
<td>Develop subjective perceptions</td>
</tr>
<tr>
<td><strong>Employees</strong></td>
<td>Work within the System</td>
<td>Meet, exceed or fail to meet technical standards</td>
</tr>
</tbody>
</table>

Are these system outputs positively, negatively or un-associated?
However, if one simply assesses the correlation between preventable adverse events and patient perceptions of care, one leaves out the possibility that other factors may influence one or both variables. It is therefore necessary to factor other control variables into the model. A correlation between preventable adverse events and patient perceptions of care would be consistent with open systems theory and the congruence model after accounting for various control variables where the two system outputs arrive at similar conclusions of system congruence despite measuring mostly different aspects of the system.

Therefore, the research hypotheses are as follows:

H1: Preventable adverse events will be significantly correlated with patient perceptions of care at the inpatient unit sub-system level. The direction of this correlation will depend on the DV being measured. HCAHPS Survey
Scores as the DV would be expected to have a negative correlation with preventable adverse events. However, a count of patient complaints would be expected to have a positive correlation. This hypothesis can be expressed using the following linear equation where, $y = \text{patient perceptions of care}$, $\beta_0 = \text{the y axis intercept}$, $x_1 = \text{preventable adverse events}$ with a corresponding beta coefficient of $\beta_1$ and $u = \text{residual}$:

$$y = \beta_0 + \beta_1x_1 + u$$

**H2:** The predictive value of the model will be improved after controlling variables from the categories of patient acuity, unit churn, patient time on the unit, and clinical staffing.

**H3:** Preventable adverse events will continue to be significantly correlated to patient perceptions of care at the inpatient unit sub-system level after controlling for select CVs.

H2 and H3 can be expressed by building on the simple linear equation used to test H1 and adding control variables ($x_2...x_i$) to the model and calculating the control variables’ standard beta coefficients ($\beta_2...\beta_i$):

$$y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \beta_ix_i + u$$

**H4:** RN Staffing CVs (X) that are significantly correlated with patient perceptions of care (Y) and preventable adverse events (Z) will be shown to be partially mediated by preventable adverse events (Z). This hypothesis can be expressed by:

**Correlation (X,Y) > Correlation (X,Y|Z) after controlling for Z**
H1-H4 suggests Patient Perceptions of Care (DV) and Preventable Adverse Events (IV) are correlated despite measuring two different components of care. The DV is measuring a subjective component of care while preventable adverse events are measuring a technical component. Since both variables are outputs from the same system and thus produced or influenced by the same people, processes, and structures the two outputs should be correlated. To the extent that a correlation of patient- and employee-driven system outputs can be shown using sample data, hospital managers will have additional insights that can assist in prioritizing areas of needed improvement. To the extent no correlation is shown or the correlation is in the opposite direction predicted then additional research would be warranted to explore why patient and employee driven outputs do not draw the similar interpretations of system congruence.

In summary, the study hypotheses suggest that preventable adverse events and patient perceptions of care are strong barometers of system congruence. Hypotheses further suggest that an assessment of system congruence would be similar even if measuring different outputs of the same system. Known clinical quality issues, therefore, would indicate to the manager that not only is the patient at risk for a poor quality outcome, but the patient is also likely to rate the unit poorly or log a complaint. Similarly, patients whose perceptions of care are not met might be at greater risk for a preventable adverse event. Managers’ understanding of this correlation may provide a more complete insight into inpatient unit system congruence and a roadmap to focus improvement efforts.
Study Population and Data

Historical data for the proposed study was drawn from Denver Health (DH) admitted patients for the years 2011, 2012, and 2013. DH is a large level 1 trauma academic safety net integrated health system located in Denver, CO. DH operates a closed system where physicians are employed by DH and on the faculty at the University of Colorado Denver. In addition to physicians, DH has 5,300 full-time equivalent employees. As a point of reference, in 2012 DH treated 160,000 unique patients, or 25% of the Denver population. In 2012, DH had 26,000 inpatient admissions. This study focused on admitted patients and included both inpatients and observation patients. DH has 22 inpatient units. Appendix C identifies the names of the inpatient units.

The analysis was a cross-sectional time series. A cross-sectional design was used because the study was based on observations that occurred naturally without experimental interference; the time series was used to ensure sufficient observations to test the research questions. Data were summarized at the inpatient unit level, and no patient identifiers or patient level data were included in the data set. Both patient perception and adverse event data were derived from actual inpatient care that occurred during the above mentioned timeframes. Brief descriptions of the data are included below.

Variables for this study were categorized into the following three categories: Dependent (DV), Independent (IV), and Control Variables (CV).
**Dependent Variables**

HCAHPS overall satisfaction rating (*HCAHPS TopBox Score*) and a count of patient complaints (*Complaints*) were the two DVs.

The first DV, *HCAHPS TopBox Score*, is an overall satisfaction rating. This overall satisfaction rating was drawn from the HCAHPS patient experience survey. The HCAHPS survey measures multiple aspects of patient perceptions. To comply with HCAHPS, DH uses a 35 question survey administered by an outside, third-party vendor, HealthStream. Patients were called directly by representatives of HealthStream, and the survey was completed over the phone. For the purpose of this study, the question pertaining to overall satisfaction was used. This question is rated on a scale from 1–10 and asks patients to rate their overall satisfaction with the care they received. Results are reported as a percentage and made available to DH on a real-time basis. Data were summarized on a monthly basis by inpatient unit and provided to the researcher by DH’s Director overseeing the patient experience office. No patient-level data or other protected health information were provided.

Healthstream representatives recommended a response rate of 10 or more in any given month for any given inpatient unit in order to be included in the study. This recommendation was followed.

The second DV, *Complaints*, is a log of patient complaints which is updated by the patient advocacy staff at DH. Complaints are entered into an electronic system by patient representatives. Complaints can be submitted though telephone, email, walk-in, or written letter. Patient representatives enter all complaints and make no judgments regarding whether or not the complaint has merit. There are brochures on each unit of DH
that have instructions and contact information for patients to connect with a patient representative. Complaints are logged by category, date, and location. For the purpose of this study, a simple count of all patient complaints across all categories and all inpatient units was used.

*Independent Variables*

The independent variable of interest was preventable adverse events. Preventable adverse events can be identified through voluntary reporting, manual chart review, or automated rule-based chart review. Given the concern for under-reporting by employees using voluntary reporting systems, and the difficulty, labor intensity and subjectivity of gathering data through chart extraction, automated rule-based chart reviews were used to collect data for this study. For this study, an existing tool developed at DH was used; this tool automatically searches clinical databases based on a set of predefined clinical triggers. This internally developed tool is called the Global Safety Score (GSS). The validity of the GSS preventable adverse event triggers were based on an internal review of the literature, CMS specifications for never events, AHRQ’s patient safety indicators, and Leapfrog’s specification manual (Sabel, 2014). Triggers are organized around eight categories: Abnormal Glucose, Hematology, Infection Control, Medication Management, Nursing, Operating Room and Procedures, Failure to Rescue or Readmission, and Other Events. The reliability of the triggers was tested through two separate pilots and a comprehensive go-live resulted in modifications to the GSS that improved the linkage to the proper attending physician, removed five criteria, and modified four criteria (Sabel, 2014). Appendix D has a summary of the GSS tool. Using GSS, this study identified the
count of preventable adverse events by patient, by inpatient unit, by month as the IV 
(PAE by Patient).

Control Variables

The final variables for this study were CVs. CVs help explain variations between the DV and IV variable of interest and potentially provide a better predictor of the DV. Borrowing from Tabachnick and Fidell (2013) control variables were selected for this study that reflected the following characteristics: intuitive, readily available, low cost to gather, reliable, theoretically important, and supported by the literature (Tabachnick & Fidell, 2013). Control variables for this study included Casemix Index, Discharges, Average Length of Stay, and three clinical staffing control variables: RN HPPD (Hours Per Patient Day), RN Staff Variance and RN Experience.

Casemix Index was used to control for patient acuity. The more acute patients are the more complex the system needs to be to care for them; therefore, the more opportunities exist for mistakes and unmet needs. It can therefore be expected that the complexity of the patient’s care can potentially impact the amount of preventable adverse events and patient perceptions of care. Casemix index is a relative weight of the resources needed to care for a particular inpatient diagnosis. Casemix index is based on risk adjusted Diagnostic Related Groups (DRGs) weights. CMS uses 745 DRG codes. DH has casemix index calculated at the inpatient unit for each month and year of the study. Casemix index is stored electronically and can be easily retrieved. The calculation for casemix index is broadly accepted and evenly applied by DH. Finally, there is support for casemix index in the literature. For example, Kane, Maciejewski, and Finch (1997)
compared patient satisfaction to patient outcomes controlled for casemix index as a confounder. Casemix index is not a clinical measure of acuity but rather a financial measure. It is, however, used in clinical billing to differentiate patients based on their diagnosis and the associated complexities of care.

In addition to resource consumption described above, the movement of patients on and off a unit results in spikes in demand for RN and other clinician time and attention. The more patient movement (or churn) exists, the more opportunities there are for employee mistakes and patient dissatisfaction. It can be expected that the level of churn on the inpatient unit can potentially impact the amount of preventable adverse events and patient perceptions of care and therefore needs to be controlled for in the model. Discharges are an adequate proxy for inpatient unit churn. DH has discharge counts by inpatient unit for each month and year of the study. Discharge data are stored electronically and can be easily retrieved. Finally, there is support for discharges in the literature. For example, Duffield, Diers, Aisbett, and Roche (2009) studied patient churn (which included admissions, discharges, and transfers) and its impact on casemix index, quality, and efficiency metrics. The authors determined that churn did indeed adversely impact nurse quality and efficiency outcome measures. Patient transfer data were not included in the current study due to DH analyst concerns with the accuracy of the data.

The longer a patient remains on the inpatient unit the more opportunities exist for employee mistakes to occur and patients to be dissatisfied. Average Length of Stay was used to control for Patient Time on Unit. It can be expected that the average length of stay on the inpatient unit can potentially impact the amount of preventable adverse events and patient perceptions of care and therefore needs to be controlled for in the model.
Average length of stay is a straightforward calculation derived from dividing the total patient days for a particular time period by the number of unique patients on the unit. DH has average length of stay calculated at the inpatient unit for each month and year of the study. For this study, average length of stay was calculated specifically for each inpatient unit and not summarized based on discharge unit. Average length of stay is stored electronically and can be easily retrieved. The calculation for average length of stay is broadly accepted and evenly applied by DH. Finally, there is support for average length of stay in the literature. For example, Tokunaga and Imanaka (2002) found a statistically significant correlation between some aspects of patient satisfaction and average length of stay.

RN clinical staffing is the final category of CVs. Not surprisingly, many of aspects of RN care have been studied in the literature as it relates to patient experience and quality. Lynn Unruh, Professor of Health Management and Informatics at the University of Central Florida, examined the major studies and summarized the statistical relationship between the clinical staffing condition (e.g., skill mix, nurse hours per patient day, etc) and the dependent variable of interest (Unruh, 2008). The findings were equivocal. For example, Cho, Ketefian, Barkauskas, and Smith (2003) found no significance between falls and hours of RN staffing, while Dunton, Gajewski, Taunton, and Moore (2004) found a significant negative correlation between patient falls on inpatient units and RN hours. Despite the inconclusiveness in these findings, there is support in the literature that the hours of RN care (Dunton et al., 2004; Lang, Hodge, Olson, Romano, & Kravitz, 2004; Whitman, Kim, Davidson, Wolf, & Wang, 2002); the
level of RN care to the proportion of patients (Krauss et al., 2005); and the experience of RNs (Hall, Doran, & Pink, 2004) are statistically related to adverse patient events.

The following variables were used to control for RN staffing:

RN HPPD (RN Hours per patient day): This variable represents the RN hours worked on the inpatient unit for a 24 hour period averaged for each patient day, each month. The metric only includes bedside RN caregivers and not RN nurse educators, RN managers, non-RN licensed personnel, etc.

RN Staff Variance: DH uses nurse to patient ratio guides to help determine needed staffing on any given day or shift. Both the desired and actual RN staffing is recorded as hours per patient day. Using the desired RN HPPD staffing as the ideal, the difference between the two measures shows actual RN HPPD in relation to the target where a positive number represents hours in excess of the target (i.e., overstaffed) and negative number represents hours that fall short of the target (i.e., understaffed). DH maintains these data for every day for every inpatient unit for each month and year of the study. These data are stored electronically and can be easily retrieved. The calculation for these two measures is based on hours per patient day and consistently applied across all time periods of the study.

RN Experience: The years of nurse experience often differs greatly across inpatient units. To control for the impact that nurse experience may have on patient perceptions of care and the volume and severity of preventable adverse events, the average number of years of RN Experience were included as a control variable. These data were gathered from internal DH human resource systems. The calculation is a weighted average; it is calculated by taking the number of hours worked in a given month
by each RN and multiplying those hours by the years of RN Experience (i.e., the number of years from the time of the original RN license to the date associated with the particular record) and dividing the product by the total RN hours in the month.

Each variable is summarized below in Table 3.

Table 3

*Summary of Study Variables*

<table>
<thead>
<tr>
<th>MODEL INPUT</th>
<th>DESCRIPTION</th>
<th>CV CATEGORY</th>
<th>DATA TYPE</th>
<th>REASON FOR INCLUSION</th>
</tr>
</thead>
<tbody>
<tr>
<td>DV1</td>
<td>HCAHPS TopBox Score</td>
<td>NA</td>
<td>Continuous</td>
<td>System Output</td>
</tr>
<tr>
<td>DV2</td>
<td>Complaints</td>
<td>NA</td>
<td>Continuous/Discrete</td>
<td>System Output</td>
</tr>
<tr>
<td>IV</td>
<td>PAE by Patient</td>
<td>NA</td>
<td>Continuous/Discrete</td>
<td>System Output</td>
</tr>
<tr>
<td>CV1</td>
<td>Casemix Index</td>
<td>Acuity</td>
<td>Continuous/Discrete</td>
<td>Explanatory</td>
</tr>
<tr>
<td>CV2</td>
<td>Discharges</td>
<td>Churn</td>
<td>Continuous/Discrete</td>
<td>Explanatory</td>
</tr>
<tr>
<td>CV3</td>
<td>Average Length of Stay</td>
<td>Time on Unit</td>
<td>Continuous</td>
<td>Explanatory</td>
</tr>
<tr>
<td>CV4</td>
<td>RN HPPD</td>
<td>Staffing</td>
<td>Continuous</td>
<td>Explanatory</td>
</tr>
<tr>
<td>CV5</td>
<td>RN Staff Variance</td>
<td>Staffing</td>
<td>Continuous</td>
<td>Explanatory</td>
</tr>
<tr>
<td>CV6</td>
<td>RN Experience</td>
<td>Staffing</td>
<td>Continuous</td>
<td>Explanatory</td>
</tr>
</tbody>
</table>

Methods of Analysis

Simple and multiple regressions and an analysis of partial correlation statistical techniques were employed in this study to address the research questions. According to Tabachnick and Fidell (2013) simple regression is well-suited to test the relationship between a single IV and DV while multiple regression is well-suited to investigate the relationships between DV and multiple IVs. Partial correlation analysis is designed to understand the level of mediation between two related variable while controlling for a third variable (i.e., the potential mediator).

The issue of statistical power was relevant to this study. Although more sophisticated methods exist, Tabachnick and Fidell (2013) offer two rules of thumb for
determining how many cases are necessary given a set amount of IVs: (1) \( N \geq 50 + 8m \) (m=number of IVs) in studies assessing multiple correlations, and (2) \( N \geq 104 + m \) in studies attempting to test individual predictors (Tabachnick & Fidell, 2013). Seven IV and CVs were used in the study, thus requiring a minimum of 106 records for multiple regression \((50 + (7 \times 8))\) and a minimum of 111 records for testing of the IV and CVs \((104 + 7)\). Both of these minimums were met. The final data set used for comparison contained 238 records for analysis of HCAHPS TopBox Score and 311 records for analysis of Complaints.

These steps were followed to complete the analysis:

**Step 1 – Gather the data**

The data needed for this study were gathered solely from DH. Time periods included the years 2011–2013. All data were provided on a monthly basis at the inpatient unit level. Table 4 shows the source of the study variables.

**Table 4**

**Source of Study Variables**

<table>
<thead>
<tr>
<th>Description</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>HCAHPS TopBox Score</td>
<td>Health Stream customer portal</td>
</tr>
<tr>
<td>Complaints</td>
<td>RL Solutions</td>
</tr>
<tr>
<td>Preventable Adverse Events</td>
<td>Global Safety Score, pulled from internal Denver Health data warehouse</td>
</tr>
<tr>
<td>Casemix Index</td>
<td>Siemens Invision, pulled from internal Denver Health data warehouse</td>
</tr>
<tr>
<td>Discharges</td>
<td>Monthly Management Information Report, pulled from internal Denver Health data warehouse</td>
</tr>
<tr>
<td>Average Length of Stay</td>
<td>Monthly Management Information Report, pulled from internal Denver Health data warehouse</td>
</tr>
<tr>
<td>RN HPPD (Hours Per Patient Day)</td>
<td>API Time and Attendance</td>
</tr>
<tr>
<td>RN Staff Variance</td>
<td>API Time and Attendance</td>
</tr>
<tr>
<td>RN Experience</td>
<td>Lawson, human resource system</td>
</tr>
</tbody>
</table>

**Step 2 – Combine the information**
Data from the various database systems were combined into a single database. For this study, Year, Month, and Inpatient Unit Identifier were used to match each disparate record.
Step 3 – Address outliers

Data outliers were identified and investigated. Treatment of outliers varied depending on whether the outlier was a verifiable mistake in the source data or an accurate reflection of the variable being measured.

Step 4 – Validate the control variables

The inclusion of each CV was supported in the literature. In addition, Pearson’s correlation coefficient with a 2-tailed test was used to determine the correlation among the CVs to each of the DVs. An initial analysis of data was conducted to make two determinations:

1. Inclusion of the CV in the model based on the unique CV’s correlation to each of the two DVs. Correlated variables p(2-tailed)<.2 were considered for inclusion in the model.

2. Inclusion of the CV in the model based on the unique CV’s correlation to the other CVs. Highly correlated CVs (>=0.8) were considered for exclusion from the model based on a potential redundant contribution to the results.

The decision tree (Figure 6) summarizes the two decisions. It was necessary to run each of the CVs two times through the decision tree for each of the two DVs, i.e., HCAHPS TopBox Score and Complaints.
**Step 5 – Determine descriptive statistics**

Descriptive statistics were performed on the combined data set for each DV using the selected IV of interest. Results of this analysis were evaluated for reasonableness.

**Step 6 – Run the regression**

Each of the four hypotheses was evaluated for both of the DVs. A simple regression model was used to address H1. A multiple regression model was used to address H2 and H3. Partial correlation analysis was used to address H4. The models were built sequentially and adapted to each of the four hypotheses. For all multiple regression modeling, the variables were entered simultaneously rather than sequentially.

**Step 7 – Interpret results and develop conclusions**

*Figure 6. Control variable validation.*
Results were evaluated against the two DVs for each of the four study hypotheses and documented. Conclusions were developed, summarized and documented.
CHAPTER 4

RESULTS AND FINDINGS

Study Population Characteristics and Descriptive Statistics

Data for this study were gathered across three years (2011–2013) from seven separate data sources (Table 4). Data sources were combined into a single file using year, month, and unit code as a unique key identifier. The new combined data file contained 1,404 records. The combined data set included 792 (56%) records pertaining to inpatient care (Table 5).

Table 5

*Case Type Breakout*

<table>
<thead>
<tr>
<th>Unit Type</th>
<th>N</th>
<th>Percent</th>
<th>Cumulative Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ancillary</td>
<td>108</td>
<td>7.7</td>
<td>7.7</td>
</tr>
<tr>
<td>Inpatient</td>
<td>792</td>
<td>56.4</td>
<td>64.1</td>
</tr>
<tr>
<td>Other</td>
<td>72</td>
<td>5.1</td>
<td>69.2</td>
</tr>
<tr>
<td>Outpatient</td>
<td>432</td>
<td>30.8</td>
<td>100.0</td>
</tr>
<tr>
<td>Total</td>
<td>1404</td>
<td>100.0</td>
<td></td>
</tr>
</tbody>
</table>

Two data sets were created from the 792 inpatient records: one for each of the two DVs, *HCAHPS TopBox Score* and *Complaints*.

*HCAHPS TopBox Score*

The following data filters were applied to inpatient data in order to finalize the data set used to evaluate the relationship between *PAE by Patient* (IV) and *HCAHPS TopBox Score* (DV):
• Repurposed inpatient units (i.e., units that switched patient population type over the course of the study) -- Excluded

• DV – HCAHPS TopBox Score – Not Blank

• DV – HCAHPS TopBox Score – survey respondents >9 for any given month and unit.

Results of these three screens are shown in Figure 7.

![Diagram showing data set filters](image)

**Figure 7.** HCAHPS TopBox Score data set filters.

Data outliers were checked against original data sources and evaluated for accuracy and, where appropriate, corrected. Outliers deemed accurate and reflective of real world outcomes were left in the data set unchanged. No outliers were deleted, and no transformations to address outliers or normality were performed on the data set.
Prior to any statistical analysis, CVs were identified and included in the data set based on intuitive sense, availability, low cost to gather, reliability, theoretical importance, and support in the literature (Tabachnick & Fidell, 2013). The CVs selected based on the above criteria were then evaluated on two additional criterion: correlation with the DV, assessed on a Pearson correlation coefficient significant at p(2-tailed)<.2 and correlation between the CVs, assessed on a Pearson’s correlation coefficient < .8.

A bivariate 2-tailed Pearson’s correlation coefficient was performed in SPSS comparing HCAHPS TopBox Score with each of the six proposed CVs: Casemix Index, Discharges, Average Length of Stay, RN HPPD, RN Staff Variance, and RN Experience.

Results for this analysis with HCAHPS TopBox Score are shown in Table 6.

Table 6

**CV Correlation Coefficients with the HCAHPS TopBox Score Data Set**

<table>
<thead>
<tr>
<th>Variables</th>
<th>HCAHPS TopBox Score</th>
<th>PAE by Patient</th>
<th>Casemix Index</th>
<th>Discharges</th>
<th>Average Length of Stay</th>
<th>RN HPPD</th>
<th>RN Staff Variance</th>
<th>sig. (2-tailed) with TopBox</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAE by Patient</td>
<td>-.168**</td>
<td>.045</td>
<td>.087</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.010</td>
</tr>
<tr>
<td>Casemix Index</td>
<td>-.065</td>
<td>.744**</td>
<td>.028</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.490</td>
</tr>
<tr>
<td>Discharges</td>
<td>-.133*</td>
<td>.406**</td>
<td>.066</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.317</td>
</tr>
<tr>
<td>Average Length</td>
<td>.187**</td>
<td>-.353**</td>
<td>-.164*</td>
<td>-.523**</td>
<td>.025</td>
<td></td>
<td></td>
<td>.004</td>
</tr>
<tr>
<td>RN HPPD</td>
<td>- .086</td>
<td>.341**</td>
<td>.134*</td>
<td>.292**</td>
<td>.291**</td>
<td>-.175**</td>
<td></td>
<td>.187</td>
</tr>
<tr>
<td>RN Staff Variance</td>
<td>.164*</td>
<td>-.327**</td>
<td>.201**</td>
<td>-.512**</td>
<td>.232**</td>
<td>.587**</td>
<td>-.208**</td>
<td>.011</td>
</tr>
<tr>
<td>RN Experience</td>
<td>.164*</td>
<td>-.327**</td>
<td>.201**</td>
<td>-.512**</td>
<td>.232**</td>
<td>.587**</td>
<td>-.208**</td>
<td>.011</td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
c. Listwise N=238

Using Pearson’s correlation coefficient test, Casemix Index and Discharges did not meet the criteria of p(2-tailed)<.2. However, these CVs were not excluded from the
data set given their statistically significant correlation with other variables. The test for collinearity between the CVs showed all CVs with correlation coefficients <.8. In light of these results and the subsequent interpretation, no proposed CVs were excluded from the *HCAHPS TopBox Score* data set prior to the development of the regression models.

The final HCAHPS TopBox Score data set contained 238 records. Records were divided 79, 83, and 76 across the years 2011 through 2013, respectively. There were eight separate inpatient units represented in the final data set comprised of six med/surg. units containing 80% of the records, one pediatric unit with 15% of the records, and one critical care unit with the remaining 5%. There were no missing values in the final data set. Relevant descriptive statistics can be found in Table 7.

Table 7

*Descriptive Statistics for HCAHPS TopBox Score Data Set*

<table>
<thead>
<tr>
<th>Variables</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>HCAHPS TopBox Score</td>
<td>.33</td>
<td>.95</td>
<td>.70</td>
<td>.1</td>
</tr>
<tr>
<td>PAE by Patient</td>
<td>0</td>
<td>37</td>
<td>14.5</td>
<td>8.0</td>
</tr>
<tr>
<td>Casemix Index</td>
<td>.94</td>
<td>3.51</td>
<td>1.58</td>
<td>.4</td>
</tr>
<tr>
<td>Discharges</td>
<td>54</td>
<td>286</td>
<td>137.7</td>
<td>44.0</td>
</tr>
<tr>
<td>Average Length of Stay</td>
<td>1.57</td>
<td>9.53</td>
<td>4.4</td>
<td>1.3</td>
</tr>
<tr>
<td>RN HPPD</td>
<td>5</td>
<td>16</td>
<td>7.7</td>
<td>2.6</td>
</tr>
<tr>
<td>RN Staff Variance</td>
<td>-6.29</td>
<td>3.30</td>
<td>0.0</td>
<td>1.1</td>
</tr>
<tr>
<td>RN Experience</td>
<td>2.3</td>
<td>7.7</td>
<td>4.4</td>
<td>1.1</td>
</tr>
<tr>
<td>Valid N</td>
<td>238</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Complaints

The following data filters were applied to inpatient data in order to finalize the data set used to evaluate the relationship between PAE by Patient (IV) and Complaints (DV):

- Repurposed inpatient units (i.e., units that switched patient population type over the course of the study) -- Excluded
- DV – Complaints – Not Blank
- *No missing values across any the DV, IV, and CVs*

Results of these three screens are shown in Figure 8.

*Figure 8. Complaints data set filters.*
Data outliers were compared to original data sources and evaluated for accuracy and, where appropriate, corrected. Outliers deemed accurate and reflective of real world outcomes were left in the data set unchanged. No outliers were deleted, and no transformations to address outliers or normality were performed on the data set.

Similar to the HCAHPS TopBox Score data file, CVs were evaluated on two criterion: correlation with Complaints, assessed on the significance of the correlation coefficient of $p(2$-tailed$)<.2$ and correlation between the CVs, assessed on a Pearson’s correlation coefficient $< .8$.

A bivariate 2-tailed Pearson’s correlation coefficient was performed in SPSS comparing Complaints with each of the six proposed CVs: Casemix Index, Discharges, Average Length of Stay, RN HPPD, RN Staff Variance, and RN Experience. Results of this analysis with Complaints are shown in Table 8.

Table 8

CV Correlation Coefficients with the Complaints Data Set

<table>
<thead>
<tr>
<th>Variables</th>
<th>Complaints</th>
<th>PAE by Patient</th>
<th>Casemix Index</th>
<th>Discharges</th>
<th>Average Length of Stay</th>
<th>RN HPPD</th>
<th>RN Staff Variance</th>
<th>RN Experience</th>
<th>sig. (2-tailed) with Complaints</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAE by Patient</td>
<td>.403**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.000</td>
</tr>
<tr>
<td>Casemix Index</td>
<td>-.089</td>
<td>-.279**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.115</td>
</tr>
<tr>
<td>Discharges</td>
<td>.376**</td>
<td>.670**</td>
<td>-.553**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.000</td>
</tr>
<tr>
<td>Average Length of Stay</td>
<td>-.157**</td>
<td>-.348**</td>
<td>.836**</td>
<td>-.718**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.005</td>
</tr>
<tr>
<td>RN HPPD</td>
<td>-.345**</td>
<td>-.452**</td>
<td>.535**</td>
<td>-.781**</td>
<td>.696**</td>
<td></td>
<td></td>
<td></td>
<td>.000</td>
</tr>
<tr>
<td>RN Staff Variance</td>
<td>.101</td>
<td>.133*</td>
<td>.223**</td>
<td>-.029</td>
<td>.245**</td>
<td>.158**</td>
<td></td>
<td></td>
<td>.074</td>
</tr>
<tr>
<td>RN Experience</td>
<td>-.315**</td>
<td>-.330**</td>
<td>.594**</td>
<td>-.730**</td>
<td>.686**</td>
<td>.734**</td>
<td></td>
<td></td>
<td>.039</td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
c. Listwise N=311
Using Pearson’s correlation coefficient test, all the CVs, when compared to the DV, met the threshold for inclusion in the study of \( p(2\text{-tailed})<.2 \). For collinearity, *Casemix Index* had a Pearson’s correlation coefficient of .836 with *Average Length of Stay* and was not significantly correlated with the DV *Complaints*. However, *Casemix Index* was not removed from the data set given its significant correlation with the IV of interest, *PAE by Patient*. In light of these results and the subsequent interpretation, no proposed CVs were excluded from the *Complaints* data set prior to the development of the regression models.

The final *Complaints* data set contained 311 records. The records were split 95, 108, and 108 across the years 2011 through 2013, respectively. There were nine separate inpatient units represented in the final data set comprised of five med/surg. units containing 58% of the records, one pediatric unit with 11% of the records, and three critical care units with the remaining 31%. There were no missing values in the final data set. Relevant descriptive statistics can be found in Table 9.
Table 9

*Descriptive Statistics for Complaints Data Set*

<table>
<thead>
<tr>
<th>Variables</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complaints</td>
<td>0</td>
<td>10</td>
<td>1.6</td>
<td>1.7</td>
</tr>
<tr>
<td>PAE by Patient</td>
<td>0</td>
<td>31</td>
<td>11.0</td>
<td>6.6</td>
</tr>
<tr>
<td>Casemix Index</td>
<td>.82</td>
<td>6.08</td>
<td>2.03</td>
<td>1.1</td>
</tr>
<tr>
<td>Discharges</td>
<td>8</td>
<td>227</td>
<td>100.0</td>
<td>54.6</td>
</tr>
<tr>
<td>Average Length of Stay</td>
<td>1.1</td>
<td>30.0</td>
<td>8.1</td>
<td>7.7</td>
</tr>
<tr>
<td>RN HPPD</td>
<td>5.5</td>
<td>19.4</td>
<td>9.9</td>
<td>4.2</td>
</tr>
<tr>
<td>RN Staff Variance</td>
<td>-.63</td>
<td>3.3</td>
<td>0.0</td>
<td>1.1</td>
</tr>
<tr>
<td>RN Exp</td>
<td>2.7</td>
<td>12.1</td>
<td>5.6</td>
<td>2.0</td>
</tr>
<tr>
<td>Valid N</td>
<td>311</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Model Design**

Simple and multiple regression models were developed in SPSS to test the first three hypotheses. The models were built sequentially and adapted to each of the three hypotheses associated with the research question one and two. For the multiple regression model, the IV and all CVs were entered simultaneously rather than sequentially. Standardized beta (β) was reported in all instances as a more meaningful representation of the results. A partial correlation analysis in SPSS was used to address the fourth hypothesis. The results organized by each of the four hypotheses are found below.
Regression and Partial Correlation Analyses and Results

Hypothesis 1 (H1)

Research question 1 asked whether preventable adverse events and patient perceptions of care are correlated at the inpatient unit level. Hypothesis 1 (H1) pertaining to this research question stated that preventable adverse events will be significantly correlated with patient perceptions of care at the inpatient unit sub-system level. The direction of this correlation will be negative when comparing PAE by Patient to HCAHPS TopBox Score and will be positive when comparing PAE by Patient to Complaints. This hypothesis can be expressed using the following variables within a simple linear regression equation where, $y = HCAHPS \ TopBox \ Score$, $\beta_0 = \text{the y axis intercept}$, $x_1 = \text{PAE by Patient}$ with a corresponding coefficient of $\beta_1$ and $u = \text{residual}$:

$$Model \ 1: \ y = \beta_0 + \beta_1x_1 + u$$

Two simple regressions were performed using Model 1 for each of the DV data sets. Both regressions were performed using SPSS. These models are designated Model 1 (HCAHPS) and Model 1 (Complaints) representing the HCAHPS TopBox Score and Complaints data set, respectively. For both DVs, Model 1 was shown to have a linear relationship with IV. The mean value for the residuals was zero. Homoscedasticity was shown to exist after an examination of the DV residuals.

HCAHPS data set. Table 10 shows the results of Model 1 (HCAHPS), and includes correlations coefficients between the variables, $\beta$ coefficient, $R$, $R^2$, and adjusted $R^2$.  

58
Table 10

Model 1 (HCAHPS) Simple Regression of PAE by Patient on HCAHPS TopBox Score

<table>
<thead>
<tr>
<th>Variables</th>
<th>HCAHPS TopBox Score Cor. Coef.</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAE by Patient</td>
<td>-0.168**</td>
<td>-0.168**</td>
</tr>
<tr>
<td>Intercept</td>
<td>.742</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.028</td>
<td></td>
</tr>
<tr>
<td>adjusted $R^2$</td>
<td>0.024</td>
<td></td>
</tr>
<tr>
<td>$R$</td>
<td>.168**</td>
<td></td>
</tr>
</tbody>
</table>

a. Predictors: (Constant), PAE by Patient

**p<.01

The estimate for $\beta$ is -.168 with p<.01. The R value was also significantly different from zero with $F(1, 236) = 6.829, p < .05$. The values for $R^2$ and adjusted $R^2$ were .028 and .024, respectively. The adjusted $R^2$ of .024 suggests that slightly more than 2% of the variability in patient experience HCAHPS TopBox Scores is predicted by PAE by Patient.

The results of Model 1 (HCAHPS) can be expressed as $[\text{HCAHPS TopBox Score} = .742 + -.168 (\text{PAE by Patient}) + u]$. The negative $\beta$ supports Hypothesis (H1) that states patient perceptions of care as measured by HCAHPS TopBox Scores will be negatively correlated with preventable adverse events as measured by PAE by Patient. Model 1 (HCAHPS) can be interpreted to read that for every one standard deviation change increase in PAE by Patient, HCAHPS TopBox Scores will decrease by 17%. 
Complaints data set. Table 11 shows the results of Model 1 (Complaints), and includes correlations coefficients between the variables, $\beta$ coefficient, $R$, $R^2$, and adjusted $R^2$.

Table 11

**Model 1 (Complaints) Simple Regression of PAE by Patient on Complaints**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Complaints Cor. Coef.</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAE by Patient</td>
<td>0.403**</td>
<td>.403**</td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td>.460</td>
</tr>
<tr>
<td>$R^2$</td>
<td></td>
<td>.162</td>
</tr>
<tr>
<td>adjusted $R^2$</td>
<td></td>
<td>.159</td>
</tr>
<tr>
<td>$R$</td>
<td></td>
<td>.403**</td>
</tr>
</tbody>
</table>

a. Predictors: (Constant), PAE by Patient

**p<.01

The estimate for $\beta$ is .403 with $p<.01$. The $R$ value was also significantly different from zero with $F(1, 309) = 59.79, p < .01$. The values for $R^2$ and adjusted $R^2$ were .162 and .159, respectively. The adjusted $R^2$ of .159 suggests that roughly 16% of the variability in patient experience Complaints is predicted by PAE by Patient.

The results of Model 1 (Complaints) can be expressed as $[Complaints = .460 + .403 (PAE by Patient) + u]$. The significant positive $\beta$ supports Hypothesis (H1) that states patient perceptions of care as measured by Complaints will be significantly correlated with preventable adverse events as measured by PAE by Patient. Model 1 (Complaints) can be interpreted to read that for every one standard deviation change increase in PAE by Patient, the number of Complaints will increase by 0.4.
Hypothesis 2 (H2)

H2 builds upon H1. Most of the variability in the DVs for Model 1 was captured in the residual and not explained by PAE by Patient. H2 defined CVs and posited that the predictive value of the Model 1 will be improved after controlling variables from the categories of patient acuity, unit churn, patient time on the unit, and clinical staffing. H2 can be expressed using multiple regression and adding Casemix Index, Discharges, Average Length of Stay, RN HPPD, RN Staff Variance, and RN Experience from the above categories respectively as CVs ($x_2...x_i$) and calculating the CVs’ beta coefficients ($\beta_2...\beta_i$) to Model 1:

Model 2: $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_i x_i + u$

Two multiple regressions were performed using Model 2 for each of the DV data sets. The regression was performed using SPSS. These models are designated Model 2 (HCAHPS) and Model 2 (Complaints) representing the HCAHPS TopBox Score and Complaints data set, respectively.

HCAHPS data set. Table 12 shows the results of Model 2 (HCAHPS) and includes correlations coefficients between the variables, $\beta$ coefficient, semi-partial correlations ($sr^2$), R, $R^2$, and adjusted $R^2$. It is important to note, the semi-partial correlations represent the amount $R^2$ would be reduced if the variable were omitted from the model.
Table 12

**Model 2 (HCAHPS) Multiple Regression of PAE by Patient on HCAHPS TopBox Score with CVs**

<table>
<thead>
<tr>
<th>Variables</th>
<th>HCAHPS TopBox Score</th>
<th>PAE by Patient</th>
<th>Casemix Index</th>
<th>Discharges</th>
<th>Average Length of Stay</th>
<th>RN HPPD</th>
<th>RN Staff Variance</th>
<th>RN Experience</th>
<th>( \beta )</th>
<th>( sr^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAE by Patient</td>
<td>-.168**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.247</td>
<td>.014</td>
</tr>
<tr>
<td>Casemix Index</td>
<td>-.045</td>
<td>.087</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.020</td>
<td>.000</td>
</tr>
<tr>
<td>Discharges</td>
<td>-.065</td>
<td>.744**</td>
<td>.028</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.274*</td>
<td>.017</td>
</tr>
<tr>
<td>Average Length of Stay</td>
<td>-.133*</td>
<td>.406**</td>
<td>.300**</td>
<td>-.066</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.044</td>
<td>.001</td>
</tr>
<tr>
<td>RN HPPD</td>
<td>.187**</td>
<td>-.353**</td>
<td>-.164*</td>
<td>-.523**</td>
<td>.025</td>
<td></td>
<td></td>
<td></td>
<td>.155</td>
<td>.012</td>
</tr>
<tr>
<td>RN Staff Variance</td>
<td>-.086</td>
<td>.341**</td>
<td>.134</td>
<td>.292**</td>
<td>.291*</td>
<td>-.175**</td>
<td></td>
<td></td>
<td>-.009</td>
<td>.000</td>
</tr>
<tr>
<td>RN Experience</td>
<td>.164*</td>
<td>-.327**</td>
<td>.201**</td>
<td>-.512**</td>
<td>.232**</td>
<td>.587**</td>
<td>-.208**</td>
<td></td>
<td>.145</td>
<td>.010</td>
</tr>
<tr>
<td>Intercept =</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.550</td>
<td></td>
</tr>
</tbody>
</table>

\( R^2 = .084 \)
\[ \text{adjusted } R^2 = .056 \]
\[ R = .289** \]

\( \text{a. Predictors: (Constant), RN Experience, Casemix Index, RN Staff Variance, PAE by Patient, Average Length of Stay, RN HPPD, Discharges} \)

The R value for the regression was significantly different from zero with \( F(7, 230) = 3.005, p < .01 \). The values for \( R^2 \) and adjusted \( R^2 \) were .084 and .056, respectively. The adjusted \( R^2 \) of .056 suggests that slightly more than 6% of the variability in patient experience HCAHPS TopBox Score is predicted by PAE by Patient, Casemix Index, Discharges, Average Length of Stay, RN HPPD, RN Staff Variance, and RN Experience. However, only Discharges had a \( \beta \) coefficient significantly different from zero.

Discharges had a \( sr^2 \) of .017. This value is the amount of variability represented by regression \( R^2 \) that is directly attributable to Discharges. The remaining .067 of \( R^2 \) (.084 - .017) is the amount of variability that all of the other variables jointly contribute to
Model 2 (HCAHPS). Although there is a negative, non-significant correlation coefficient between Discharges and the DV, when combined into Model 2 (HCAHPS), Discharges becomes a significant predictor and the direction changes from negative to positive.

Collinearity was again tested as part of Model 2 (HCAHPS). SPSS output included variance inflation factor (VIF). A threshold of >10 was used to determine collinearity among the CVs. No two control variables exhibited VIF >10.

The adjusted $R^2$ of .056 for Model 2 (HCAHPS) was more than double that of Model 1 (HCAHPS) which had an adjusted $R^2$ of .024. The increase in adjusted $R^2$ indicates that the variables added to Model 2 (HCAHPS) resulted in an improved model for predicting HCAHPS TopBox Scores. This finding supports H2 which posited that the addition of select CVs would improve the overall predictive results of Model 1 (HCAHPS).

Complaints data set. Table 13 shows the results of Model 2 (Complaints) and includes correlations coefficients between the variables, $\beta$ coefficient, semi-partial correlations ($sr^2$), $R$, $R^2$, and adjusted $R^2$. 


The R value for the regression was significantly different from zero with F(7,303) = 13.7, p < .01. The values for R² and adjusted R² were .240 and .222, respectively.

The adjusted R² of .222 suggests that slightly more than 22% of the variability in patient experience Complaints is predicted by PAE by Patient, Casemix Index, Discharges, Average Length of Stay, RN HPPD, RN Staff Variance, and RN Experience. Three variables, PAE by Patient with p<.01, RN HPPD with p<.05, and RN Experience with p<.05, had a β coefficient significantly different from zero.

The sum of the sr² for PAE by Patient, RN HPPD and RN Experience was .069.

This value is the amount of the variability represented by regression R² that is directly attributable to the three significant variables in Model 2 (Complaints). The remaining
.171 of $R^2 (.240 - .069)$ is the amount of variability that all of the other non-significant variables jointly contribute to Model 2 (Complaints).

Collinearity was again tested as part of Model 2 (Complaints). SPSS output included VIF. A threshold of >10 was used to determine collinearity among the CVs. No CVs exhibited a VIF >10.

The adjusted $R^2$ for Model 2 (Complaints) was .222. The adjusted $R^2$ for Model 1 (Complaints) was .159. The increase in adjusted $R^2$ indicates that the variables added to Model 2 (Complaints) resulted in an improved model for predicting Complaints. This finding supports H2 which posited that the addition of select CVs would improve the overall predictive results of Model 1 (Complaints).

**Hypothesis 3 (H3)**

Hypothesis 3 (H3) posits that preventable adverse events will continue to be significantly correlated to patient perceptions of care at the inpatient unit sub-system level after controlling select CVs.

**HCAHPS data set.** H3 was not supported by Model 2 (HCAHPS). The beta coefficient for $PAE$ by $Patient$ was not significant at $p<.05$. The loss of significance was not limited to $PAE$ by $Patient$. In addition, $Average$ $Length$ $of$ $Stay^*$, $RN$ $HPPD^{**}$ and $RN$ $Exp^*$ all had significant correlation coefficients with the DV ($^*p(2$-tailed)$<.05$ and $^{**}p(2$-tailed)$<.01$) and yet yielded no statistical significance when entered into Model 2 (HCAHPS).
However, within Model 2 (HCAHPS) *Casemix Index, Average Length of Stay, and RN Staff Variance* had \(sr^2\) values at or near zero. The removal of *Casemix Index, Average Length of Stay, and RN Staff Variance* would presume to improve the adjusted \(R^2\) and thus the overall predictive performance of Model 2 (HCAHPS). A revised Model 2 (HCAHPS) was performed with *Casemix Index, Average Length of Stay, and RN Staff Variance* removed from the model. Table 14 shows the results of revised Model 2 (HCAHPS) and includes correlations coefficients between the variables, \(\beta\) coefficient, semi-partial correlations (\(sr^2\)), \(R\), \(R^2\), and adjusted \(R^2\).

Table 14

*Revised Model 2 (HCAHPS): Casemix Index, Average Length of Stay and RN Staff Variance Removed*

<table>
<thead>
<tr>
<th>Variables</th>
<th>HCAHPS TopBox Score</th>
<th>PAE by Patient Discharges</th>
<th>RN HPPD</th>
<th>(\beta)</th>
<th>(sr^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAE by Patient</td>
<td>-.168</td>
<td>-.296**</td>
<td></td>
<td>0.039</td>
<td></td>
</tr>
<tr>
<td>Discharges</td>
<td>-.065</td>
<td>.744</td>
<td>.309**</td>
<td>0.033</td>
<td></td>
</tr>
<tr>
<td>RN HPPD</td>
<td>.187</td>
<td>-.353</td>
<td>-.523</td>
<td>.171*</td>
<td>0.017</td>
</tr>
<tr>
<td>RN Experience</td>
<td>.164</td>
<td>-.327</td>
<td>-.512</td>
<td>.587</td>
<td>.124</td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td></td>
<td></td>
<td>.525</td>
<td></td>
</tr>
</tbody>
</table>

\[ R^2 = .082 \]
\[ \text{adjusted } R^2 = .066 \]
\[ R = .286^{**} \]

*Predictors: (Constant), RN Experience, PAE by Patient, RN HPPD, Discharges*

\(*p<.05\)

\(\text{**p}<.01\)

The revised Model 2 (HCAHPS) results were strikingly different. Adjusted \(R^2\) increased from .056 in Model 2 (HCAHPS) to .066 in revised Model 2 (HCAHPS). \(R\) remained significant at \(F (4, 233) = 5.203, p<.01\). Three of the four regression
\( \beta \) coefficients differed significantly from zero: \textit{PAE by Patient} with \( p<.01 \), \textit{Discharges} with \( p<.01 \), and \textit{RN HPPD} with \( p<.05 \). \textit{RN Experience} did not individually contribute significantly to the regression.

The results of revised Model 2 (HCAHPS) support H3 that states preventable adverse events will remain significantly negatively correlated to patient perceptions of care at the inpatient unit sub-system level after controlling for several additional CVs.

\textit{Complaints data set}. H3 was supported by Model 2 (Complaints) the \( \beta \) coefficient for \textit{PAE by Patient} significant at \( p<.01 \). Although \textit{Discharges} at \( p(2\text{-tailed})<.01 \) and \textit{Average Length of Stay} at \( p(2\text{-tailed})<.01 \) had significant bi-variate correlation coefficients with the DV, neither were significantly correlated with the DV inside of Model 2 (Complaints).

A further examination of the results showed \textit{Discharges} and \textit{RN Variance} had \( \text{sr}^2 \) values at or near zero. Given these results, the removal of \textit{Discharges} and \textit{RN Variance} from Model 2 (Complaints) would presume to improve the adjusted \( R^2 \) and thus the overall predictive performance of Model 2 (Complaints). A revised Model 2 (Complaints) was performed with \textit{Discharges} and \textit{RN Variance} removed from the model. Table 15 shows the results of revised Model 2 (Complaints) and includes correlations coefficients between the variables, \( \beta \) coefficient, semi-partial correlations (\( \text{sr}^2 \)), \( R \), \( R^2 \), and adjusted \( R^2 \).
The revised Model 2 (Complaints) results were slightly improved over Model 2 (Complaints). Adjusted $R^2$ increased from .222 in Model 2 (Complaints) to .226 in revised Model 2 (Complaints). $R$ remained significant at $F(5, 305) = 19.096, p<.01$.

Three of the five regression $\beta$ coefficients differed significantly from zero: $PAE$ by Patient with $p<.01$, $RN$ HPPD with $p<.05$, and $RN$ Experience with $p<.01$. $Casemix$ Index and Average Length of Stay did not individually contribute significantly to the regression.

The results of revised Model 2 (Complaints) continued to support H3 that states preventable adverse events will remain significantly negatively correlated to patient perceptions of care at the inpatient unit sub-system level after controlling for several additional CVs.

### Table 15
*Revised Model 2 (Complaints): Discharges and RN Variance Removed*

<table>
<thead>
<tr>
<th>Variables</th>
<th>Complaints</th>
<th>$\beta$</th>
<th>PAE by Patient</th>
<th>$s^2$</th>
<th>Casemix Index</th>
<th>Average Length of Stay</th>
<th>RN HPPD</th>
<th>$s^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAE by Patient</td>
<td>.03</td>
<td>.323**</td>
<td>.083</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Casemix Index</td>
<td>-.09</td>
<td>.113</td>
<td>.04</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Length of Stay</td>
<td>-.16</td>
<td>.164</td>
<td>.06</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RN HPPD</td>
<td>-.35</td>
<td>-.193*</td>
<td>.01</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RN Experience</td>
<td>-.31</td>
<td>-.247**</td>
<td>.023</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Intercept = 1.946

- $R^2 = .238$
- Adjusted $R^2 = .226$
- $R = .488**$

a. Predictors: (Constant), RN Exp, PAE by Patient, Casemix Index, RN HPPD, Average Length of Stay

*p<.05

**p<.01
Hypothesis 4 (H4)

The third research question explored the extent to which the correlation between the clinical staffing variables and patient perceptions of care are mediated by preventable adverse events. Hypothesis 4 (H4) posits that RN Staffing CVs (X) that are significantly correlated with patient perceptions of care (Y) and preventable adverse events (Z) will be shown to be partially mediated by preventable adverse events (Z). This hypothesis can be expressed by:

Model 3: Correlation (X,Y) > Correlation (X,Y|Z) after controlling for Z

Two partial correlation analyses were performed using Model 3 for each of the DV data sets. The analysis was performed using SPSS. These models are designated Model 3 (HCAHPS) and Model 3 (Complaints) representing the HCAHPS TopBox Score and Complaints data set, respectively.

For partial correlation to be shown, four conditions must be met:

1. (X,Y) X and Y must be correlated
2. (X,Z) X and Z must be correlated
3. (X,Y|Z) X and Y after controlling for Z must be correlated
4. (X,Y) > (X,Y|Z) the correlation of X and Y after controlling for Z must be reduced from the initial correlation of X and Y.

(Tabachnick & Fidell, 2013)

*RN HPPD* and *RN Experience* were the two RN staffing variables that met the first two criterions and therefore were included in this analysis. *RN Staff Variance* was not significantly correlated with either DV and therefore was omitted from the analysis.
HCAHPS data set. Table 16 shows the partial correlation output for RN HPPD and HCAHPS TopBox Score controlling for PAE by Patient. Table 17 shows the same analysis for RN Experience.

Table 16

Partial Correlation Output for RN HPPD and HCAHPS TopBox Score

<table>
<thead>
<tr>
<th>Condition</th>
<th>Relationship</th>
<th>Correlation</th>
<th>sig.</th>
<th>Condition Met?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(X,Y): (RN HPPD, HCAHPS TopBox Score)</td>
<td>.187**</td>
<td>.004</td>
<td>Y</td>
</tr>
<tr>
<td>2</td>
<td>(X,Z): (RN HPPD, PAE by Patient)</td>
<td>-.353**</td>
<td>.010</td>
<td>Y</td>
</tr>
<tr>
<td>3</td>
<td>(X,Y</td>
<td>Z): (RN HPPD, HCAHPS TopBox Score</td>
<td>PAE by Patient)</td>
<td>.139*</td>
</tr>
<tr>
<td>4</td>
<td>(X,Y) &gt; (X,Y</td>
<td>Z) and still significant</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the .05 level (2-tailed)

Table 17

Partial Correlation Output for RN Experience and HCAHPS TopBox Score

<table>
<thead>
<tr>
<th>Condition</th>
<th>Relationship</th>
<th>Correlation</th>
<th>sig.</th>
<th>Condition Met?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(X,Y): (RN Experience, HCAHPS TopBox Score)</td>
<td>.164*</td>
<td>.011</td>
<td>Y</td>
</tr>
<tr>
<td>2</td>
<td>(X,Z): (RN Experience, PAE by Patient)</td>
<td>-.327**</td>
<td>.000</td>
<td>Y</td>
</tr>
<tr>
<td>3</td>
<td>(X,Y</td>
<td>Z): (RN Experience, HCAHPS TopBox Score</td>
<td>PAE by Patient)</td>
<td>.117</td>
</tr>
<tr>
<td>4</td>
<td>(X,Y) &gt; (X,Y</td>
<td>Z) and still significant</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the .05 level (2-tailed)

The partial correlation analysis showed the correlation between RN HPPD and HCAHPS TopBox Score to be partially mediated by PAE by Patient. This conclusion supports H4. The analysis did not show partial mediation between RN Experience and HCAHPS TopBox Score. However, the analysis does imply full mediation between RN Experience and HCAHPS TopBox Score by PAE by Patient given the correlation between
RN Experience and HCAHPS TopBox Score was eliminated after controlling for PAE by Patient.

Complaints data set. Re-running the analysis with the Complaints data set shows the partial correlation output for RN HPPD and Complaints controlling for PAE by Patient (Table 19). Table 20 shows the same analysis for RN Experience and Complaints controlling for PAE by Patient.

Table 18

Partial Correlation Output for RN HPPD and Complaints

<table>
<thead>
<tr>
<th>Condition</th>
<th>Relationship</th>
<th>Correlation</th>
<th>sig.</th>
<th>Met?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(X,Y): (RN HPPD, Complaints)</td>
<td>-.345**</td>
<td>.000</td>
<td>Y</td>
</tr>
<tr>
<td>2</td>
<td>(X,Z): (RN HPPD, PAE by Patient)</td>
<td>-.452**</td>
<td>.000</td>
<td>Y</td>
</tr>
<tr>
<td>3</td>
<td>(X,Y</td>
<td>Z): (RN HPPD, Complaints</td>
<td>PAE by Patient)</td>
<td>-.200**</td>
</tr>
<tr>
<td>4</td>
<td>(X,Y) &gt; (X,Y</td>
<td>Z) and still significant</td>
<td>**</td>
<td>Y</td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (2-tailed).

Table 19

Partial Correlation Output for RN Experience and Complaints

<table>
<thead>
<tr>
<th>Condition</th>
<th>Relationship</th>
<th>Correlation</th>
<th>sig.</th>
<th>Met?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(X,Y): (RN Experience, Complaints)</td>
<td>-.315**</td>
<td>.000</td>
<td>Y</td>
</tr>
<tr>
<td>2</td>
<td>(X,Z): (RN Experience, PAE by Patient)</td>
<td>-.330**</td>
<td>.000</td>
<td>Y</td>
</tr>
<tr>
<td>3</td>
<td>(X,Y</td>
<td>Z): (RN Experience, Complaints</td>
<td>PAE by Patient)</td>
<td>-.211**</td>
</tr>
<tr>
<td>4</td>
<td>(X,Y) &gt; (X,Y</td>
<td>Z) and still significant</td>
<td>**</td>
<td>Y</td>
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**. Correlation is significant at the 0.01 level (2-tailed).
The partial correlation analysis showed the correlation between *RN HPPD* and *Complaints* and *RN Experience* and *Complaints* to both be partially mediated by *PAE by Patient*. This conclusion supports H4.
CHAPTER 5
SUMMARY AND CONCLUSIONS

Summary of Study Findings

The purpose of the study was to provide healthcare managers with additional insights regarding the congruence and ultimately the performance of hospital inpatient units. Open systems theory and a congruence model provided a conceptual framework with which to analyze inpatient unit congruence. These theoretical frameworks suggested that outputs from the same system would arrive at the same conclusion regarding system congruence even if the outputs were measuring different aspects of care.

Preventable adverse events and patient perceptions of care are two measures of system outputs that measure different aspects of the hospital environment. Researchers have demonstrated that preventable adverse events are a measure of the technical aspects of care while patient perceptions of care tend to measure more subjective aspects of care (Covinsky et al., 1998; Levinson & General, 2010; Press, 2014). The prevalence of preventable adverse events would suggest a lack of organizational congruence. Similarly, poor patient perceptions would indicate an undesired system output and therefore a lack of congruence. Given that preventable adverse events and patient perceptions of care are outputs from the same system, it may be expected that these two outputs are correlated with one another.

The following four hypotheses were developed and tested to explore the question of correlation between different system outputs.

H1: Preventable adverse events will be significantly correlated with patient perceptions of care at the inpatient unit sub-system level.
H2: The predictive value of the model will be improved after controlling variables from the categories of patient acuity, unit churn, patient time on the unit, and clinical staffing.

H3 Preventable adverse events will continue to be significantly correlated to patient perceptions of care at the inpatient unit sub-system level after controlling select CVs.

H4: RN Staffing CVs (X) that are significantly correlated with patient perceptions of care (Y) and preventable adverse events (Z) will be shown to be partially mediated by preventable adverse events (Z).

The IV of interest was a count of preventable adverse events measured by the variable PAE by Patient. There were two DVs used in the study: the HCAHPS TopBox Score and a count of patient Complaints. A unique data set was created for each DV. All hypotheses were tested against each data set. Finally, there were six CVs that were used to help test the hypotheses. These CVs were Casemix Index, Discharges, Average Length of Stay, RN HPPD, RN Staff Variance, and RN Experience. All data were summarized by month, by year, and by inpatient unit.

A simple regression model (Model 1) was used to test the relationship between the IV PAE by Patient and the two DVs: HCAHPS TopBox Score and Complaints. Standardized beta ($\beta$) was reported in all instances as a more meaningful representation of the results. The results from the regression supported H1 finding PAE by Patient was significantly correlated to both HCAHPS TopBox Score ($\beta p<.05$) and Complaints ($\beta p<.01$). Interpretation of both models suggest that for every one standard deviation increase in PAE by Patient, the HCAHPS TopBox Score will decrease by ~17% and
Complaints will increase by ~.5. The starting point or Y intercept for both DVs was 74.2% for HCAHPS TopBox Score and 0.5 for Complaints.

The direction of the $\beta$ coefficients for Model 1 (HCAHPS) and Model 1 (Complaints) is logical and consistent with H1. The $\beta$ coefficient for Model 1 (HCAHPS) is negative implying that as preventable adverse events increase, the HCAHPS TopBox Score will decrease. Conversely, the $\beta$ coefficient for the Model 1 (Complaints) is positive implying that as preventable adverse events increase, complaints will increase.

Although the correlation between the IV and both DVs was shown to be significant, the relatively low adjusted $R^2$ of .024 for Model 1 (HCAHPS) and .159 for Model 1 (Complaints) suggests that most of the explanation of variability in the two DVs is found in the residual of the model. This conclusion is consistent with the literature that a patient’s perception of his or her care is based on more than the technical delivery of the care.

The second hypothesis was tested using a multiple regression model (Model 2). As noted above, although a significant correlation exists between the IV and two DVs, most of the variability in the DVs was unexplained and contained in the residual. Therefore, Model 2 was developed to help interpret some of the unexplained variability and test H2 which posited that the predictive value of Model 1 will be improved by adding select CVs. Results from Model 2 (HCAHPS) and Model 2 (Complaints) support H2. This conclusion was derived by analyzing adjusted $R^2$. Adjusted $R^2$ measures the amount of variability in the DV explained by the IVs. Unlike $R^2$, adjusted $R^2$ can increase or decrease as IVs are added to the model. The initial adjusted $R^2$ of .024 for Model 1 (HCAHPS) increased to .056 after adding the CVs. Similarly, the adjusted $R^2$ of .159 for
Model 1 (Complaints) increased to .222 after adding the CVs. This increase in adjusted 
$R^2$ showed that the predictive value of the model was improved by adding the CVs. This 
result was consistent with H2 and expected given all CVs used in the study were 
supported in the literature as associated with either preventable adverse events, patient 
perceptions of care, or both. It was logical, therefore, to conclude that the inclusion of 
these CVs in the model would improve the predictability of the model.

Results for H3 were mixed. H3 posited that the IV would remain statistically 
significant with both DVs after controlling for select CVs. PAE by Patient was not 
significantly correlated with HCAHPS TopBox Score after adding the CVs. However, 
PAE by Patient continued to be significantly correlated with Complaints after adding the 
CVs.

A review of Model 2 (HCAHPS) results showed Discharges to be the only CV 
with a significant correlation to HCAHPS TopBox Score. Interestingly, Average Length of 
Stay*, RN HPPD**, and RN Exp* all had significant bi-variate correlations with 
HCAHPS TopBox Score (*p(2-tailed)<.05 and **p(2-tailed)<.01) prior to entering the 
variables into the model, but no statistical significance after being entered into the model. 
The results suggest that some of the variables were confounders impacting the IV, DV, 
and other CVs. Additionally, output from Model 2 (HCAHPS) suggested that some of the 
CVs were extraneous to the model. A review of the semi-partial correlations ($sr^2$) (i.e., 
the amount of the explained variation in $R^2$ uniquely attributable to an individual 
variable) showed three variables with $sr^2$ values at or near zero, Casemix Index, Average 
Length of Stay, and RN Staff Variance. A revised Model 2 (HCAHPS) was conducted 
after omitting these three variables.
Results for revised Model 2 (HCAHPS) reversed the previous results and supported H3. Under this revised model the $\beta$ coefficient for PAE by Patient remained significant at p<.01 with HCAHPS TopBox Score. In addition, the adjusted $R^2$ in the revised model increased to .066 from .056. Although the revised Model 2 (HCAHPS) was an improvement over Model 2, it still only predicted 7% of the variability of HCAHPS TopBox Score.

As noted above, prior to any revisions, H3 was supported by Model 2 (Complaints) with PAE by Patient remaining significant at p<.01. However, similar to Model 2 (HCAHPS) a review of the semi-partial correlations ($sr^2$) in Model 2 (Complaints) showed two extraneous variables, Discharges and RN Staff Variance, with $sr^2$ values at or near zero. Given these two extraneous variables, a revised Model 2 (Complaints) was run after omitting these two variables. The omission of Discharges and RN Staff Variance resulted in a minor improvement to the overall predictive value of the Model 2 (Complaints). The $\beta$ coefficient for PAE by Patient remained significant at p<.01. However, revised Model 2 (Complaints) did improve the significance of the $\beta$ coefficient for RN Experience from p<.05 to p<.01. Adjusted $R^2$ in the revised model increased slightly to .226 from .222.

H4 posited that the relationship between the RN staffing CVs and the DVs would be partially mediated by PAE by Patient. RN HPPD and RN Experience were singled out for this analysis because of statistical significance with the IV and both DVs, as well as the strong support in the literature regarding staffing’s effect on both the technical and subjective aspects of patient care (Unruh, 2008). This partial mediation analysis was designated Model 3.
PAE by Patient was shown to partially mediate the significant relationship between RN HPPD and both DVs: HCAHPS TopBox Score and Complaints. In addition, PAE by Patient was shown to partially mediate the significant relationship between RN Experience and Complaints. These results support H4. However, the relationship between RN Experience and HCAHPS TopBox Score was not partially mediated by PAE by Patient. Rather it was fully mediated by PAE by Patient. This result, although interesting, does not support H3.

Table 20 shows a summary of results for each data set and research hypothesis.

Table 20

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Relevant CV</th>
<th>Model</th>
<th>DV - HCAHPS TopBox Score</th>
<th>DV - Complaints</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>NA</td>
<td>1</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H2</td>
<td>NA</td>
<td>2</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H3</td>
<td>NA</td>
<td>2</td>
<td>Not Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H3</td>
<td>NA</td>
<td>2-revised</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H4</td>
<td>RN HPPD</td>
<td>3</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H4</td>
<td>RN Experience</td>
<td>3</td>
<td>Not Supported</td>
<td>Supported</td>
</tr>
</tbody>
</table>

Limitations

The study was conducted using data from Denver Health, a large academic medical center in Denver, Colorado. The results, therefore, pertain to a single institution and cannot be assumed to apply to other organizations.

Although preventable adverse event counts and CVs were available for every inpatient unit for every month of the study, HCAHPS TopBox Scores were not available for every unit for every month. Therefore, the availability HCAHPS TopBox Score on a
unit and monthly basis dictated the ultimate size of the data set for this DV. The data set related to *Complaints* was similarly constrained.

The literature supports the notion that preventable adverse events measure technical outputs of the care system while patient perceptions of care measure more subjective outputs of the care system. However, the two variables are not uniquely distinct. It is entirely possible that a patient who completed a HCAHPS survey did so with direct knowledge of a preventable adverse event that occurred during his or her hospital stay. Similarly, it is a reasonable assumption that a patient might file a complaint as a direct result of being informed of a preventable adverse event. In both cases, the patient’s awareness of the preventable adverse event would presumably be a factor in the patient’s rating of the overall performance of the hospital and/or the filing of the complaint. However, the retrospective data available at DH did not support an analysis that would link individual patients who incurred a preventable adverse event with their subsequent HCAHPS survey results. Although possible, DH does not currently link patients’ filing complaints with clinical outcomes of care.

Staffing differences and resource allocations exist in hospitals from shift to shift. It is possible that these differences across a 24 hour period could positively or negatively impact a patient’s perception of care or the number of preventable adverse events. However, the DV, IV, and all of the CVs with the exception of *RN HPPD* were not available on a shift basis thus preventing any analysis of shift impacts on the DV.

Although DH management was not aware of any instance of this issue, it was not possible to determine if staff members on any given unit, in any given time period, overtly or inadvertently encouraged or discouraged patients from filing a complaint.
Finally, for patients who visited multiple units it was not possible to determine if their comments reflected care provided in inpatient units other than the discharge unit. This is a universal constraint of patient experience data. As such, it is acknowledged as a study limitation.

Recommendations for Future Research

Recommendation 1: Replicate this study at other academic institutions to see if similar results are obtained.

Recommendation 2: Given the relatively small adjusted $R^2$ for the HCAHPS TopBox data set, conduct additional research on other potential control variables, e.g., patient transfers between units and unit level manager.

Recommendation 3: Re-test the hypotheses with other system outputs such as workforce engagement survey results and/or culture of patient safety survey results.

Recommendation 4: Explore research questions using more granular aspects of the data, e.g., preventable adverse events by trigger type, complaints by category, and/or different HCAHPS questions.

Recommendation 5: Test findings outside of traditional inpatient care. For example, research organizations with different business models such as freestanding procedural centers.
Conclusions

System outputs as measured by preventable adverse events and patient perceptions of care are correlated at DH both before and after controlling for variables related to patient acuity, unit churn, patient time on unit, and RN staffing. This correlation implies that although preventable adverse events and patient perceptions of care are measuring mostly different aspects of care, the measures arrive at the same conclusion regarding inpatient unit congruence. In other words, if the system is not producing safe patient care, then it is not producing an exceptional patient experience and vice versa.

This conclusion seems somewhat logical, but not altogether expected. Irwin Press (2014), one of the founders of the patient satisfaction survey firm Press Ganey, argued that it is entirely plausible that an organization known for high clinical outcomes might provide poor patient service. This may be so, however, at DH at the inpatient unit level, low incidents of preventable adverse events were not correlated with low patient experience scores or high incidence of complaints.

The value of this study is more than an understanding of correlation between two system outputs. Now that a correlation has been established, the real value comes from the application of this information. At DH, the screening tool used to identify and count preventable adverse events can be run on an almost real time frequency including while the patient is still in the hospital. Therefore, spikes in preventable adverse events can be identified almost immediately providing management a timely alert to intervene not only for clinical quality reasons, but also for patient experience reasons. Specifically, preventable adverse event data could be used as a leading indicator for management,
providing insights into potential patient experience issues long before survey results become available or complaints are filed. Use of this information in the form of timely and effective intervention by management has the potential to change the opinion of the patient before the patient responds to the HCAHPS Survey and potentially eliminate the need for a patient to file a complaint.

The conclusions of this study may help identify problems sooner, but management must still devise and implement effective counter measures to address the underlying issues. Results from Model 3 may provide insights into effective short-term and long-term management interventions. In the short-term, RN HPPD were shown to be significantly correlated with HCAHPS TopBox Scores and Complaints. Further, this relationship was shown to be mediated by PAE by Patient. Monitoring changes in RN HPPD by shift, day, and week would be expected to provide management with insights into potential increase in PAE by Patient and ultimately adverse impact HCAHPS TopBox Scores and Complaints. Similarly knowledge of the relationship between the variables would be expected to be considered prior to making changes to RN hours.

In the long-term, RN Experience was shown to be significantly correlated with HCAHPS TopBox Scores and Complaints with the relationship with HCAHPS TopBox Score fully mediated by PAE by Patient with Complaints partially mediated by PAE by Patient. These relationships highlight the importance of RN tenure in reducing preventable adverse events and improving the patient experience. Management efforts aimed at reducing unwanted RN turnover or hiring more experienced RNs would presumably decrease preventable adverse events and thus improve HCAHPS survey results and reduce patient complaints.
In summary, the results of this study suggest that management at DH would be well-advised to better use and dissect the data that are already available to them. While not implying any claim of causality, by studying the data results from one aspect of care, management can glean important insights that will help them improve another.
REFERENCES


Glen, B. (2012). Cleveland Clinic negotiating health care bundled payment deal with Boeing, MedCity News.


APPENDIX A

UNIQUE CAHPS SURVEYS
- Health Plan
- Clinician and Group
- Surgical Care
- American Indian
- Dental Plan
- Experience of Care and Health Outcomes
- Home Health Care
- Hospital
- In-Center Hemodialysis
- Nursing Home

("Surveys and Guidance," 2012)
APPENDIX B

LARGEST PATIENT SATISFACTION SURVEY FIRMS
### Largest Patient-Satisfaction Measurement Firms

**Ranked by total number of engagements in 2011**

| Rank/Company                  | Headquarters   | Ownership | Total number of engagements
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>National Research Corp.</td>
<td>Lincoln, Neb.</td>
<td>Public</td>
<td>33,223</td>
</tr>
<tr>
<td>Press Ganey Associates</td>
<td>South Bend, Ind.</td>
<td>Private</td>
<td>27,304</td>
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<tr>
<td>HealthStream</td>
<td>Nashville</td>
<td>Public</td>
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<td>Professional Research</td>
<td>Omaha, Neb.</td>
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<tr>
<td>Strategic Healthcare Programs</td>
<td>Santa Barbara, Calif.</td>
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<td>3,022</td>
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<td>Deyta</td>
<td>Louisville, Ky.</td>
<td>Private</td>
<td>2,500</td>
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<td>DSS Research</td>
<td>Fort Worth, Texas</td>
<td>Private</td>
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</tr>
<tr>
<td>National Business Research Institute</td>
<td>Addison, Texas</td>
<td>Private</td>
<td>784</td>
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<tr>
<td>Sullivan Leuillin</td>
<td>San Diego</td>
<td>Private</td>
<td>754</td>
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<tr>
<td>Jackson Group</td>
<td>Hickory, N.C.</td>
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<tr>
<td>Arbor Associates</td>
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<tr>
<td>J.L. Morgan &amp; Associates</td>
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<tr>
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<td>4</td>
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</tr>
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<td>3</td>
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<td>10</td>
<td>intelligresearch.com</td>
</tr>
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**Note:** Information is self-reported from companies responding to Modern Healthcare’s survey. Only those that participated were considered for this ranking.

1. For 2011, reflects all sectors of the healthcare industry.
2. Number of U.S. consultants employed in 2011, who spent at least 50% of their time in the healthcare industry.
3. All figures are estimates.  
4. Taxable, not-for-profit organization.  
5. Private, not-for-profit organization.

**Source:** Modern Healthcare’s 2012 Patient Satisfaction Measurement Firms Survey

Information in this chart subsequently may be revised at the discretion of the editor.

For more information regarding our research, contact the Research Department at research@modernhealthcare.com or 312-649-5459.

For more charts, lists, rankings and survey results, visit modernhealthcare.com/data.
APPENDIX C

DENVER HEALTH INPATIENT UNITS AND GROUPINGS
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<th>MasterUnitAbbrev</th>
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<tr>
<td>3PCU</td>
<td>Progressive Care Unit 3</td>
<td>Inpatient</td>
</tr>
<tr>
<td>4B</td>
<td>Med Surg 4B</td>
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</tr>
<tr>
<td>5A</td>
<td>Acute Eating Disorder 5A</td>
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</tr>
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<td>6A</td>
<td>Med Surg 6A</td>
<td>Inpatient</td>
</tr>
<tr>
<td>7A</td>
<td>Med Surg 7A</td>
<td>Inpatient</td>
</tr>
<tr>
<td>8A</td>
<td>Med Surg 8A</td>
<td>Inpatient</td>
</tr>
<tr>
<td>9A</td>
<td>Med Surg 9A</td>
<td>Inpatient</td>
</tr>
<tr>
<td>ADOL</td>
<td>Adolescent Psych</td>
<td>Inpatient</td>
</tr>
<tr>
<td>ADU</td>
<td>Admission Discharge Unit</td>
<td>Inpatient</td>
</tr>
<tr>
<td>CCMFIP</td>
<td>Correctional Care Medical Facility IP</td>
<td>Inpatient</td>
</tr>
<tr>
<td>CTU</td>
<td>Clinical Transition Unit</td>
<td>Inpatient</td>
</tr>
<tr>
<td>PSY</td>
<td>Adult Psychiatric Unit East and West</td>
<td>Inpatient</td>
</tr>
<tr>
<td>LD</td>
<td>Labor and Delivery</td>
<td>Inpatient</td>
</tr>
<tr>
<td>MB</td>
<td>Mother Baby</td>
<td>Inpatient</td>
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<tr>
<td>MICU</td>
<td>Medical Intensive Care Unit</td>
<td>Inpatient</td>
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<td>NBNURS</td>
<td>New Born Nursery</td>
<td>Inpatient</td>
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</table>
APPENDIX D

GLOBAL SAFETY SCORE OVERVIEW" by A. Sabel, 2014. Reprinted with permission.

"Global Safety Score Overview" by A. Sabel, 2014. Reprinted with permission.
The Global Safety Score (GSS) was created to detect and evaluate triggers that allows for measurement of adverse events or harm in our system. It will enhance identification, prevention, and mitigation of risk. It will help to proactively identify areas for performance improvement and support “continual readiness”. It will allow for near real-time review of triggering events that may result in improved patient outcomes and a new understanding of the risk profile at our institution.

There are eight “clusters” of events that are considered of significant harm to warrant entry onto the registry. The clusters are Abnormal Glucose, Hematology, Infection Control, Medication Management, Nursing, Operating Room and Procedures, Failure to Rescue or Readmission, and Other Events.

Data is collected once a triggering event occurs for an inpatient – these items include, but are not limited to: demographic information, prior visit history, and the triggering event. Data will be updated nightly. Some triggering events will be available close to real-time whereas others will be delayed.

Triggering events are categorized as “Patient Safety Flags” (PSF) or “Patient Safety Codes” (PSC). PSFs are events that can be identified while the patient is still hospitalized. PSF events can be determined daily. PSCs are events that cannot be determined until the patient has been discharged. The PSC events are based on ICD-9-CM codes and will tie to the discharge date. The PSC events typically appear on the GSS within 10 days of discharge, but can take up to one month due to physician queries done by our coders.

The Responsible Attending is identified using our billing system. For PSC events, the Responsible Attending is the discharge attending. For PSF events, the Responsible Attending is the attending on record when the event occurred. The only exception is for the Operating Room and Procedure Cluster where the Responsible Attending is the surgeon whom performed the principal procedure. The nursing unit identified
for an event is the discharge nurse station for PSCs and the collection or testing nurse unit for PSFs.

Abnormal Glucose Cluster

Abnormal Glucose events are categorized as patient safety flags and are determined daily during a patient’s hospitalization. Low Glucose events occur for glucose <50 mg/dL and the trigger value is the lowest glucose value per day. A patient can have at most one Low Glucose event per day. Glucose labs during the first day of admission are excluded from the metric. Allowable labs for this metric include Bedside Glucose, Glucose Point of Care, Fasting Glucose, Random Glucose, and Whole Blood Glucose.

Hematology Cluster

The Hematology Cluster includes four events: elevated Partial Thromboplastin Time (PTT), elevated International Normalized Ratio (INR), Venous Thromboembolism (VTE), and Blood Incompatibility. The PTT events are patient safety flags which occur once per day and the trigger value is the highest value per day. The INR events are patient safety flags which occur once per hospitalization and the trigger value is the highest value per hospitalization. All PTT results during the admission and INR results after the first 24 hours of admission are eligible. Elevated PTT is defined as >100 seconds and elevated INR is defined as >5. VTE and Blood Incompatibility are patient safety codes which occur once per hospitalization and they are identified after the patient is discharged. Both of these events are determined using ICD-9-CM diagnosis codes. Diagnosis codes can be in any priority, i.e. principal or secondary positions. In addition, the diagnosis must be a hospital acquired condition. Venous thromboembolism includes deep vein thrombosis (DVT) and pulmonary embolus (PE). The inclusion criteria for DVT/PE
are based on the Agency for Healthcare Research and Quality (AHRQ) Patient Safety Indicator (PSI) v4.3 for DVT/PE and the criteria for Blood Incompatibility are based on the Centers for Medicare and Medicaid Services (CMS) Never Event specifications for this topic. The ICD-9 diagnosis codes for these events are listed below.

**DVT/PE**

- 415.1 – Pulmonary embolism and infarction
- 415.11 – Iatrogenic pulmonary embolism and infarction
- 415.19 – Other pulmonary embolism and infarction
- 451.11 – Phlebitis and thrombophlebitis of Femoral vein (deep or superficial)
- 451.19 – Phlebitis and thrombophlebitis of other deep vessels of lower extremities
- 451.81 – Phlebitis and thrombophlebitis of Iliac vein
- 453.40 – Acute venous embolism and thrombosis of unspecified deep vessels of lower extremity
- 453.41 – Acute venous embolism and thrombosis of deep vessels of proximal lower extremity
- 453.42 – Acute venous embolism and thrombosis of deep vessels of distal lower extremity

**Blood Incompatibility**

- 999.60 – ABO incompatibility reaction, unspecified
- 999.61 – ABO incompatibility with hemolytic transfusion reaction not specified as acute or delayed
- 999.62 – ABO incompatibility with acute hemolytic transfusion reaction
- 999.63 – ABO incompatibility with delayed hemolytic transfusion reaction
- 999.69 – Other ABO incompatibility reaction
Infection Cluster

The Infection Cluster includes *Clostridium Difficile* (C. diff) infection and central line associated blood stream infection (CLABSI). C. diff is a patient safety flag which occurs for each positive stool test during a hospitalization. This includes positive results on the C. Diff Cytotoxin test, C. Diff Cytotoxin culture, Rapid C. Diff toxin, Rapid C. Diff culture, and C. Diff Toxin B gene PCR. If only the C. diff antigen is positive on these tests, an event has not occurred.

CLABSI is a patient safety code which occurs once per hospitalization and is identified after the patient is discharged. The inclusion criterion for CLABSI is based on CMS specifications for this Never Event. The diagnosis code “999.31 – Infection due to central venous catheter” can be in any priority and must be a hospital acquired condition.

Medication Management Cluster

The Medication Management Cluster includes three events: elevated Potassium, Naloxone administration, and Flumazenil Administration. All of these events are patient safety flags which occur once per day. Elevated Potassium is defined as a serum potassium >6 mEq/L. The trigger value is the highest value per day. Potassium results during the first 24 hours of admission are excluded. Naloxone and Flumazenil are identified using our Medication Administration Check (MAC) system. Medication administrations which occur in the emergency department are excluded. Currently MAC is available in all inpatient locations except the emergency department, operating room, and post anesthesia care unit.

Nursing Cluster

The Nursing Cluster includes three events: pressure ulcers, falls and trauma, and catheter-associated urinary tract infection (CAUTI). All of these events are patient safety codes which occur once per hospitalization and are identified after the patient
is discharged. The events are determined using ICD-9-CM diagnosis codes which can be in any diagnosis position (primary or secondary) and must be hospital acquired conditions. The inclusion criteria for the events are based on the Centers for Medicare and Medicaid Services (CMS) Never Event specifications. It is important to recognize that CMS only includes ICD-9 codes that affect DRG assignment when identifying Fall and Trauma Never Events, i.e. “Major Complications and Comorbidities” (MCC) and “Complications and Comorbidities” (CC). The ICD-9 diagnosis codes for these events are listed below.

Pressure Ulcer
- 707.23 – Stage III pressure ulcer
- 707.24 – Stage IV pressure ulcer

Falls and Trauma*
- 800-829 – Fractures
- 830-839 – Dislocations
- 850-854 – Intracranial injury
- 925-929 – Crushing injury
- 940-949 – Burn
- 991-994 – Other and unspecified effects of external causes

*only codes within these ranges on the CC/MCC list are included

CAUTI
- 996.64 – Infection and inflammatory reaction due to indwelling urinary catheter

Operating Room / Procedure Cluster

The Operating Room and Procedure Cluster includes eight events: surgical site infection (SSI) due to an internal device, foreign object retained after surgery, iatrogenic pneumothorax, postoperative hemorrhage or hematoma, postoperative
respiratory failure, accidental puncture of laceration, birth trauma, and intra- or postoperative death for non-trauma patients. All of these events are patient safety codes which occur once per hospitalization and are identified after the patient is discharged. Intraoperative or postoperative deaths are determined based on a discharge disposition of death and an admission or transfer to the operating room. Patients on the trauma registry are excluded from the mortality event.

The inclusion criteria for surgical site infection due to an internal device are based on a review of literature. The inclusion criteria for foreign object retained after surgery is based on the CMS Never Events Specifications. These two events are determined using ICD-9-CM diagnosis codes which can be in any diagnosis position (primary or secondary) and must be hospital acquired conditions. The ICD-9 diagnosis codes for these events are listed below.

SSI Due to an Internal Device

- 996.60 – Infection and inflammatory reaction due to unspecified device, implant, and graft
- 996.61 – Infection and inflammatory reaction due to cardiac device, implant, and graft
- 996.62 – Infection and inflammatory reaction due to other vascular device, implant, and graft
- 996.63 – Infection and inflammatory reaction due to nervous system device, implant, and graft
- 996.65 – Infection and inflammatory reaction due to other genitourinary device, implant, and graft
- 996.68 – Infection and inflammatory reaction due to peritoneal dialysis catheter
- 996.69 – Infection and inflammatory reaction due to other internal prosthetic device, implant, and graft
Foreign Object Retained After Surgery

- 998.4 – Foreign body accidentally left during a procedure
- 998.7 – Acute reaction to foreign substance accidentally left during a procedure

The inclusion criteria for iatrogenic pneumothorax, postoperative hemorrhage, postoperative respiratory failure, accidental puncture or laceration, and birth trauma were constructed using the AHRQ PSIs. AHRQ excludes cases from the denominator of each metric based on clinical relevance. In addition, the AHRQ PSIs are limited to discharges 18 years and older defined by specific DRGs or MS-DRGs. Simplified descriptions of the AHRQ specifications for each metric are shown below. For further information, please visit the AHRQ PSI website at http://www.qualityindicators.ahrq.gov/modules/psi_overview.aspx.

Iatrogenic Pneumothorax

- Numerator: Discharges with ICD-9 code for hospital-acquired iatrogenic pneumothorax
  - 512.1 – Iatrogenic pneumothorax
- Denominator: All surgical and medical discharges age 18 years and older defined by specific DRGs or MS-DRGs.
- Exclusions:
  - Principal diagnosis of iatrogenic pneumothorax
  - MDC 14 (pregnancy, childbirth, and puerperium)
  - Diagnosis code of chest trauma or pleural effusion
  - Procedure code of diaphragmatic surgery, thoracic procedure, lung biopsy, pleural biopsy, or cardiac procedure

Postoperative Hemorrhage or Hematoma
• **Numerator:** Discharges with ICD-9 diagnosis code for hospital-acquired postoperative hemorrhage or hematoma in any secondary diagnosis field AND ICD-9 procedure code for postoperative control of hemorrhage or for drainage of hematoma
  
  o **Diagnosis Codes:**
    998.11 – Hemorrhage complicating a procedure
    998.12 – Hematoma complicating a procedure
  
  o **Procedure Codes:**
    18.09 – Other incision of external ear
    28.7 – Control of hemorrhage after tonsillectomy and adenoidectomy
    38.80 – Other surgical occlusion of unspecified site
    38.81 – Other surgical occlusion of intracranial vessels
    38.82 – Other surgical occlusion of other vessels of head and neck
    38.83 – Other surgical occlusion of upper limb vessels
    38.84 – Other surgical occlusion of abdominal aorta
    38.85 – Other surgical occlusion of thoracic vessel
    38.86 – Other surgical occlusion of abdominal arteries
    38.87 – Other surgical occlusion of abdominal veins
    38.88 – Other surgical occlusion of lower limb arteries
    38.89 – Other surgical occlusion of lower limb veins
    39.41 – Control of hemorrhage following vascular surgery
    39.98 – Control of hemorrhage not otherwise specified
    49.95 – Control of postoperative hemorrhage of anus
    54.0 – Incision of abdominal wall
    54.12 – Reopening of recent laparotomy site
    57.93 – Control of postoperative hemorrhage of bladder
    59.19 – Other incision of perivesicle tissue
60.94 – Control of postoperative hemorrhage of prostate
61.0 – Incision and drainage of scrotum and tunica and vaginalis
69.98 – Other operations on supporting structures of uterus
70.14 – Other vaginotomy
71.09 – Other incision of vulva and perineum
75.91 – Evacuation of obstetrical incisional hematoma of perineum
75.2 – Evacuation of other hematoma of vulva and vagina
86.04 – Other incision with drainage of skin and subcutaneous tissue

- **Denominator:** All surgical discharges 18 years and older defined by specific DRGs or MS-DRGs and an ICD-9 code for an operating room procedure.

- **Exclusions:**
  - Principal diagnosis of postoperative hemorrhage or hematoma
  - Procedure is postoperative control of hemorrhage or drainage of hematoma is the only operating room procedure or it occurs before the first operating room procedure
  - MDC 14 (pregnancy, childbirth, and puerperium)

**Postoperative Respiratory Failure**

- **Numerator:**
  - Discharges with ICD-9 code for hospital-acquired acute respiratory failure in any secondary diagnosis field
    - 518.81 – Acute respiratory failure
    - 518.84 – Acute and chronic respiratory failure
  - Mechanical ventilation for 96 consecutive hours or more that begins zero or more days after the first major operating room procedure
    - 96.72 – Continuous mechanical ventilation for 96 consecutive hours or more
Mechanical ventilation for less than 96 consecutive hours or undetermined that begins two or more days after the first major operating room procedure

96.70 – Continuous mechanical ventilation of unspecified duration
96.71 – Continuous mechanical ventilation for less than 96 consecutive hours

Reintubation one or more days after the first major operating room procedure

96.04 – Insertion of endotracheal tube

- Denominator: All elective surgical discharges age 18 and older defined by specific DRGs or MS-DRGs and an ICD-9 code for an operating room procedure.
- Exclusions:
  - Principal diagnosis of acute respiratory failure
  - Any diagnosis of neuromuscular disorder, craniofacial anomalies, or degenerative neurological disorder
  - Procedure for tracheostomy is the only operating room procedure or it occurs before the first operating room procedure
  - Procedure for esophageal resection, lung cancer, ENT/neck
  - MDC 14 (pregnancy, childbirth, puerperium), 4 (diseases/disorders of respiratory system), 5 (diseases/disorders of circulatory system)

Accidental Puncture of Laceration

- Numerator: Discharges with ICD-9 code denoting hospital-acquired accidental cut, puncture, perforation, or laceration during a procedure in any secondary diagnosis field
- E870.0 – Accidental cut, puncture, perforation, or hemorrhage during surgical operation
- E870.1 – Accidental cut, puncture, perforation, or hemorrhage during infusion or transfusion
- E870.2 – Accidental cut, puncture, perforation, or hemorrhage during kidney dialysis or other perfusion
- E870.3 – Accidental cut, puncture, perforation, or hemorrhage during injection or vaccination
- E870.4 – Accidental cut, puncture, perforation, or hemorrhage during endoscopic exam
- E870.5 – Accidental cut, puncture, perforation, or hemorrhage during aspiration of fluid or tissue, puncture, and catherization
- E870.6 – Accidental cut, puncture, perforation, or hemorrhage during heart catherization
- E870.7 – Accidental cut, puncture, perforation, or hemorrhage during administration of enema
- E870.8 – Accidental cut, puncture, perforation, or hemorrhage during other specified medical care
- E870.9 – Accidental cut, puncture, perforation, or hemorrhage during unspecified medical care
- 998.2 – Accidental puncture or laceration during a procedure

- Denominator: All surgical and medical discharges age 18 years and older defined by specific DRGs and MS-DRGs.

- Exclusions:
  - Principal diagnosis denoting accidental cut, puncture, perforation, or laceration
  - Diagnosis code for spine surgery
Birth Trauma

- Numerator: Discharges with ICD-9 code for birth trauma in any diagnosis field.
  - 767.0 – Subdural and cerebral hemorrhage due to trauma or to intrapartum anoxia or hypoxia
  - 767.11 – Epicranial subaponeurotic hemorrhage (massive)
  - 767.3 – Injuries to skeleton (excludes clavicle)
  - 767.4 – Injury to spine and spinal cord
  - 767.5 – Facial nerve injury
  - 767.7 – Other cranial and peripheral nerve injuries
  - 767.8 – Other specified birth trauma

- Denominator: All newborns

- Exclusions:
  - Preterm infants with a birth weight less than 2,000 grams
  - Diagnosis code of injury to brachial plexus or osteogenesis imperfecta

Readmission / Failure to Rescue Cluster

The Readmission and Failure to Rescue Cluster includes five events: all cause readmission within 7 days, eclampsia, death in patients with non-extreme severity of illness (SOI) and risk of mortality (ROM), ICU bounce-back events within 48 hours, and transfers from the ED to acute care to the ICU within 24 hours. Readmissions, eclampsia, and death are patient safety codes which occur once per hospitalization and are identified after the patient is discharged. ICU bounce-backs and transfers
from ED to acute care to ICU are patient safety flags which can be identified once during a hospitalization.

All cause 7-day readmission events require at least one hour between the admissions so that transfers to behavioral health and rehabilitation are excluded. A readmission is also excluded if the patient had an admission within the previous six months with a principal diagnosis or principal procedure of dialysis (V56 – Encounter for dialysis and dialysis catheter care, 39.95 – hemodialysis), or if the readmission was an elective admission. Readmissions after index visits for false labor are also excluded. Only the first readmission per index visit is included.

Eclampsia is determined using ICD-9-CM diagnosis codes which can be in any diagnosis position (primary or secondary) and must be hospital acquired. The ICD-9 codes are as follows.

- 642.60 – Eclampsia, unspecified as to episode of care or not applicable
- 642.61 – Eclampsia, delivered, with or without mention of antepartum condition
- 642.62 – Eclampsia, delivered, with mention of postpartum complication
- 642.63 – Eclampsia, antepartum condition or complication
- 642.64 – Eclampsia, postpartum condition of complication

Deaths occurring in patients with non-extreme SOI and ROM trigger an event. Death is determined by the discharge disposition. SOI and ROM are calculated by our 3M coding system.

ICU bounce-backs are based on bed transfers within our facility. To be eligible, a patient must be go from an ICU unit (MICU, SICU, PICU, NICU) to acute care (3B, PCU, 4B, 6A, 7A, 8A, 9A, CCMF, Rehab) or OB (PEDS, L&D, M-B), and then be transferred back to an ICU unit within 48 hours of the first ICU placement. There is a maximum of one event per hospitalization.
Transfers from the ED to acute care to ICU are based on transfers within our facility. To be eligible, a patient must be admitted through the ED and be admitted to acute care (3B, PCU, 4B, 6A, 7A, 8A, 9A, CCMF, Rehab) or OB (PEDS, L&D, M-B). The patient must then be transferred to an ICU unit (MICU, SICU, PICU, NICU) within 24 hours of arrival in the ED. There is a maximum of one event per hospitalization.

Other Triggers Cluster

The Other Triggers Cluster includes two events: air embolism, and stroke or transient ischemic attack (TIA). Air embolism and stroke/TIA are patient safety codes which occur once per hospitalization and are identified after the patient is discharged. The events are determined using ICD-9-CM diagnosis codes which can be in any priority and must be hospital acquired conditions. The inclusion criteria for air embolism are based on the CMS Never Events Specifications. Stroke and TIA specifications are based on the Leapfrog specification manual for RF32. The ICD-9 diagnosis codes for the patient safety code events are listed below.

Air Embolism

- 999.1 – Air embolism as a complication of medical care, not elsewhere classifiable

Stroke and Transient Ischemic Attack

- 430 – Subarachnoid hemorrhage
- 431 – Intracerebral hemorrhage
- 432.0 – Nontraumatic extradural hemorrhage
- 432.1 – Subdural hemorrhage
- 432.9 – Unspecified intracranial hemorrhage
- 433.01 – Occlusion and stenosis of basilar artery with cerebral infarction
- 433.11 – Occlusion and stenosis of carotid artery with cerebral infarction
- 433.21 – Occlusion and stenosis of vertebral artery with cerebral infarction
- 433.31 – Occlusion and stenosis of multiple and bilateral arteries with cerebral infarction
- 433.81 – Occlusion and stenosis of other specified precerebral with cerebral infarction
- 433.91 – Occlusion and stenosis of unspecified precerebral artery with cerebral infarction
- 434.01 – Cerebral thrombosis with cerebral infarction
- 434.11 – Cerebral embolism with cerebral infarction
- 434.91 – Cerebral artery occlusion, unspecified with cerebral infarction
- 435.0 – Transient cerebral ischemia, basilar artery syndrome
- 435.1 – Transient cerebral ischemia, vertebral artery syndrome
- 435.2 – Transient cerebral ischemia, subclavian artery syndrome
- 435.3 – Transient cerebral ischemia, vertebrobasilar artery syndrome
- 435.8 – Transient cerebral ischemia, other specified
- 435.9 – Transient cerebral ischemia, unspecified
- 436 – Acute, but ill-defined, cerebrovascular disease

Source: Denver Health Office of the Medical Director. Permission granted.
APPENDIX E

IRB APPROVALS: UNIVERSITY COLORADO DENVER
Not Human Subject Research

04-Dec-2013

Investigator: Timothy Harin

Sponsor(s): COMIRB Protocol 13-2990 Initial Application

Effective Date: 03-Dec-2013

Title: Assessing system congruence by analyzing the relationship between employee and patient driven system outputs.

Not Human Research

Your research project submitted to COMIRB under protocol number 13-2990 has been reviewed and our determination is that it is not human research as defined by our policies and current regulations and in accordance with OHRP and FDA guidelines.

Therefore, you may proceed with the project strictly following the protocol as submitted and reviewed by COMIRB. No continuing review of the project will be required, however, you must resubmit the protocol to COMIRB for approval if any substantive changes are made to the protocol in question.

Review Comments:

This protocol was submitted for Exempt review but determined to be Not Human Subject Research.

These documents were reviewed as part of this Not Human Subject Research:

- Application, dated 10/30/2013
- Response to Minor Mods v. date 11/21/2013
- Personnel-Section C, no date
- Mentor Responsibilities, no date
- Student Responsibilities, no date
- Denver Health Form, dated 11/08/2013
- Cover Letter, Dated 11/07/2013

Please note that COMIRB will no longer be E-mailing final documents. Stamped documents indicating a determination of Non-human subject research can be retrieved in the eRA (InfoEd) system. Please click here to access instructions on finding these stamped documents.

Sincerely,

UCD Panel A
APPENDIX F

IRB APPROVALS: UNIVERSITY ALABAMA BIRMINGHAM
DATE: December 20, 2013

MEMORANDUM

TO: Timothy Harlin
   Principal Investigator

FROM: Marilyn Doss, M.A.
      Vice Chair
      Institutional Review Board for Human Use (IRB)

RE: Request for Determination - Human Subjects Research
   IRB Protocol #N131209002 - Assessing System Congruence by Analyzing the Relationship Between Employee and Patient Driven System Outputs

A member of the Office of the IRB has reviewed your Application for Not Human Subjects Research Designation for above referenced proposal.

The reviewer has determined that this proposal is not subject to FDA regulations and is not Human Subjects Research. Note that any changes to the project should be resubmitted to the Office of the IRB for determination.