Published in final edited form as:

Nurs Res. 2018 ; 67(4): 314–323. doi:10.1097/NNR.0000000000000287.

Risk Adjustment for Hospital Characteristics Reduces Unexplained Hospital Variation in Pressure Injury Risk in Adult Patients in an Integrated Healthcare Delivery System

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Abstract

Background—Research investigating risk factors for hospital acquired pressure injury (HAPI) has primarily focused on the characteristics of patients and nursing staff. Limited data are available on the association of hospital characteristics with HAPI.

Objective—We aimed to quantify the association of hospital characteristics with HAPI and their impact on residual hospital variation in HAPI risk.

Method—We employed a retrospective cohort study design with split validation using hierarchical survival analysis. This study extends the analysis “Hospital Acquired Pressure Injury (HAPI): Risk Adjusted Comparisons in an Integrated Healthcare Delivery System” by Rondinelli

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Ethical Conduct of Research: The Kaiser Permanente Northern and Southern California Institutional Review Boards approved the study.

Clinical Trial Registration: Not applicable

Conflicts of Interest and Sources of Funding: The authors declare no conflicts of interest.

et al. (2017) to include hospital-level factors. We analyzed 1,661 HAPI episodes among 728,266 adult hospitalization episodes across 35 California Kaiser Permanente hospitals, an integrated healthcare delivery system, between January 1, 2013 and June 30, 2015.

Results—After adjusting for patient-level and hospital-level variables, 2 out of 12 candidate hospital variables were statistically significant predictors of HAPI. The hazard for HAPI decreased by 4.8% for every 0.1% increase in a hospital's mean mortality ([6.3%, 2.6%], $P < .001$), while every 1% increase in a hospital's proportion of patients with a history of diabetes increased HAPI hazard by 5% ([−.04%, 10.0%], $P = .072$). Addition of these hierarchical variables decreased unexplained hospital variation of HAPI risk by 35%.

Discussion—We found hospitals with higher patient mortality had lower HAPI risk. Higher patient mortality may decrease the pool of patients who live to HAPI occurrence. Such hospitals may also provide more resources (specialty staff) to care for frail patient populations. Future research should aim to combine hospital datasets to overcome power limitations at the hospital level, and should investigate additional measures of structure and process related to HAPI care.

Hospital acquired pressure injuries (HAPIs) are an important nurse-sensitive hospital quality indicator (Agency for Healthcare Research and Quality, 2014). HAPI occurrence has been associated with patient age, comorbidity, and vasopressor use in critical care (Alderden, Rondinelli, Pepper, Cummins, & Whitney, 2017). Prevention strategies include patient repositioning, skin care, nutritional support, use of specialty bed surfaces and silicon foam dressings (Chou et al., 2013; Reddy, Gill, & Rochon, 2006; Tayyib & Coyer, 2016). With a national incidence of 31 HAPIs per 1,000 discharges (Agency for Healthcare Research and Quality, 2016b), they are both a frequent occurrence and the focus of quality reporting and quality improvement activities.

Some proportion of HAPIs may be considered unavoidable (Edsberg, Langemo, Baharestani, Posthauer, & Goldberg, 2014) in the context of a patient's clinical circumstances (end of life, use of vasopressors in hemodynamically unstable patients, or reliance on medical devices for survival). Nevertheless, HAPIs are largely considered an avoidable complication. HAPIs may cause severe pain and infection, and an estimated 60,000 patients die annually as a direct consequence of pressure injuries (Agency for Healthcare Research and Quality, 2014). For hospitals and healthcare delivery systems, HAPIs (including those present on admission) increase hospital length of stay and cost with approximately \$500–70,000 per patient per pressure injury, totaling up to \$11 billion annually in the United States (National Pressure Ulcer Advisory Panel, European Pressure Ulcer Advisory Panel, & and Pan Pacific Pressure Injury Alliance, 2014). In addition, more than 17,000 HAPI lawsuits are filed annually, making it the second largest cause of hospital litigation (Agency for Healthcare Research and Quality, 2014).

Patient and Nursing Characteristics of HAPI Risk

To measure hospital quality without bias, quality agencies and health systems rely on risk-adjustment methods that control for risk factor differences in a given patient population (Iezzoni, 2013). Recent systematic reviews clearly delineate key risk factors for HAPI (Alderden et al., 2017; Beeckman, Van Lancker, Van Hecke, & Verhaeghe, 2014; Coyer &

Tayyib, 2017; Liu, He, & Chen, 2012; Michel et al., 2012; Rao, Preston, Strauss, Stamm, & Zalman, 2016). The evidence suggests that patient age, severity of illness, type 2 diabetes mellitus, renal insufficiency/renal failure, immobility, malnutrition, incontinence, cardiac surgery, a low baseline Braden scale score (Bergstrom, Braden, Laguzza, & Holman, 1987), and hemodynamic compromise may contribute to HAPI risk. A data mining study by Raju, Su, Patrician, Loan, and McCarthy (2015) found that patient mobility, serum pre-albumin, and length of stay were associated with HAPI risk. Protective nursing characteristics may include percent of nurses with a baccalaureate degree, percent of nurses with specialty certifications (Boyle et al., 2016), and the degree of nurse-perceived structural empowerment of the unit or hospital within the Magnet hospital framework (Ma & Park, 2015). Few studies to date, however, have investigated the association of hospital characteristics beyond nursing with HAPI risk (such as hospital size, location, or occupancy rate). This is problematic because risk-adjustment of HAPI without adjusting for hospital characteristics assumes that all hospitals are equal when they are truly not. Knowing which hospital variables are associated with high or low risk of HAPIs could allow health care delivery systems to modify these risk factors and take a more nuanced approach to quality improvement.

Research Objective

This report extends and expands upon an analysis by Rondinelli and colleagues titled “Hospital Acquired Pressure Injury (HAPI): Risk Adjusted Comparisons in an Integrated Healthcare Delivery System” published in *Nursing Research* in 2017. Rondinelli et al. developed a HAPI risk model with adjustment for patient-level variables using hierarchical survival analysis in Kaiser Permanente, a large integrated health care delivery system. This work found that patient age, male sex, a patient’s comorbidity burden, severity of illness at admission, total Braden scale at admission, and admit category were independently associated with HAPI. However, substantial unexplained variation in HAPI risk remained across hospitals in the health system after adjustment for patient variables.

We had two research objectives: 1) to evaluate the association of hospital characteristics with HAPI risk, and, 2) to quantify whether addition of these hospital variables would reduce residual variation. Given the scarcity of evidence investigating hospital characteristics of HAPI, this study was hypothesis generating and did not aim to test an *a priori* null hypothesis and alternative hypothesis for a specific variable or set of variables.

Theoretical Framework: Donabedian’s Structure-Process-Outcomes (SPO)

Model

The SPO model (Donabedian, 1966) is a framework for assessing the relationship between care quality and patient outcomes. The model posits that fair comparisons of care outcomes can only be achieved using empirically derived standards and consideration of all relevant measurement domains. Structural factors – which we are including as hierarchical variables in our analyses – may include a wide variety of variables, including characteristics of the care setting, human and capital resources, and work tools. Process factors are the services and tasks performed along the continuum of care delivery. They are often time-based

measures of a clinical activity relative to another (time from A to B) or expressed in binary form (task performed/not performed). Outcome measures aim to define a given clinical or organizational state in an unbiased manner, so that the measurement is a true reflection of said state.

The SPO can be aptly applied to the research question. Answering whether certain hospital characteristics (structural measures) improve between-hospital variation of HAPI risk (outcome) would account for an important, albeit understudied, factor of care. Identification of such characteristics would better enable the measurement and characterization of HAPI risk in the organization and other similar healthcare delivery systems. Consequently, results from this study have the potential to fill gaps in the field of HAPI outcomes research.

Methods

The Kaiser Permanente Northern and Southern California Institutional Review Boards approved the study.

Sample and Setting

Our study cohort consisted of 728,266 hospitalization episodes among 35 Kaiser Permanente hospitals across Northern and Southern California between January 1, 2013 and June 30, 2015, a 2.5-year timeframe. The health system uses a comprehensive electronic medical record (EMR) with standardized flowsheet documentation across sites, including the Braden scale.

Episode Inclusion and Exclusion Criteria

The eligible research population was adult patients at least 18 years of age who were admitted with an overnight stay during the study timeframe. New patients entered the cohort at any time during the study timeframe (dynamic cohort). We included multiple hospital episodes by the same patient. Sensitivity analysis confirmed episode independence for patients with more than one hospital episode. Given inter-hospital transfer within the health system, hospital episodes included concatenation of individual hospital stays, as described previously (Escobar, Gardner, Greene, Draper, & Kipnis, 2013; Escobar et al., 2008). We excluded hospitalizations that began outside of the health system, those for observation status, and episodes from labor and delivery, psychiatry and rehabilitation. Table 1 describes the cohort.

Measures

Outcome Variable—The outcome of interest was the first HAPI documented in the system's sentinel event database, irrespective of stage. Any newly documented inpatient HAPI in the health system triggers an evaluation by a licensed wound specialty nurse and stage confirmation following clinical guidelines by the National Pressure Ulcer Advisory Panel (2014).

As a second outcome, this report also aimed to determine the reduction of unexplained hospital variation of HAPI risk across the health system. In a hierarchical model, this variation is measured as the random effect of the hospitals.

Patient-Level Independent Variables—The previous study focused on patient-level predictors of HAPI risk, which included the Braden score. This model served as the baseline model for this study. Statistically and/or clinically significant patient variables included patient age, male sex, comorbidity burden (COPS2 score), severity of illness at admission (LAPS2 score), the lowest Braden score in the first 24 hours after admission, admission type (ED medical compared to ED surgical), history of Type 2 diabetes mellitus or stroke, and code status.

Composite Measures—We examined three composite measures: COPS2, LAPS2, and the Braden scale. First, the COPS2 is a risk-adjusted composite score of a patient's comorbidity burden (Escobar et al., 2013). It includes diagnosis codes from the previous twelve months prior to admission. Second, the LAPS2 score is a measurement of a patient's severity of illness incorporating vital signs and laboratory values (Escobar et al., 2012). Both COPS2 and LAPS2 have been externally validated and used in prior health services research (Stevens & Howell, 2015; van Walraven, Escobar, Greene, & Forster, 2010). Third, developed in 1987, the Braden scale (Bergstrom et al., 1987) is a composite score for HAPI risk with remarkable longevity in acute care nursing. Factors are sensory perception, moisture, activity, mobility, nutrition, and friction/shear with a score range of 6 to 23 points (lower score: higher risk). We calculated all three composite measures using EMR data.

Development and Selection of Hospital-Level Independent Variables

We defined twenty-two candidate hospital variables and evaluated their collinearity to produce candidate variables for model building. These included hospital size, admission volume, occupancy, population density of hospital's county, mean patient age, mean comorbidity score (COPS2), percent with COPS2 >65, mean severity of illness score (LAPS2), percent with LAPS2 > 110, mean length of stay, percent full code, percent long-term care discharges, percent history of diabetes, percent history of stroke, admission type, mean Braden score, mean patient mortality, percent sepsis admission, and critical care utilization. We selected hospital variables because they were meaningful at the patient level (e.g., hospital's mean patient age and patient age) or because of a plausible putative association. The Supplemental Digital Content file describes the initial set of hospital variables along with their putative associations (SDC Table 2) and the flow of variable selection (SDC Figure 1). For example, a hospital's operational capacity (occupancy) may be a risk factor given that its nursing staff is managing more admissions, transfers and discharges rather than performing direct nursing care. Conversely, a hospital serving a sicker or frailer patient population may be a protective factor because such hospitals may expend additional resources to care for these patients. After collinearity testing, twelve candidate hospital variables remained for model building (Table 2).

Model Derivation and Validation

We split our patient cohort into derivation (70% of observations) and validation (30%) datasets. Variable testing, model building, and model cross-validation occurred in the derivation set, while we reserved the validation dataset strictly for final model confirmation. We built the initial dataset using SAS 9.3 software (SAS Institute Inc. 2002–2010: Cary, NC, USA). We performed data management, variable generation, model building, and statistical analysis in STATA14 (StataCorp LP, 2015. Stata Statistical Software: Release 14. College Station, TX, USA) and R/R studio (R Core Team, 2016: R: A language and environment for statistical computing. R Foundation for Statistical Computing: Vienna, Austria. www.R-project.org; RStudio, Inc., 2016: RStudio: Integrated Development for R: Boston, MA, USA). We performed model cross-validation using SAS software and developed graphs in Tableau 9.0 software (Tableau Software Inc., 2015: Seattle, WA, USA).

Mixed Effects (Hierarchical) Survival Model

We used mixed effects survival analysis (Cleves, Gould, & Marchenko, 2016), an approach that accounts for the temporal dimension of patients entering and leaving a research cohort at different points in time. Mixed effects models analyze the observed temporal probabilities hierarchically across clusters (here: hospitals). Clustering accounts for within-hospital dependence of observations; meaning that HAPI events are correlated within a hospital and may be associated with some hospital characteristic that varies across facilities. Mixed effects survival models calculate the random effects of the clustering variable while also adjusting for the base-level variables (here: patient characteristics). This is useful for two reasons. First, a temporal analysis offers a more accurate view of a patient's clinical course (as patients stay longer, their HAPI risk increases). Second, one cannot assume that all patient episodes are independent of the hospital in which they took place.

Since a longer length of stay may increase HAPI risk, we accounted for the shrinking denominator of patients over time by right-censoring episodes by hospital discharge as a competing risk (discharges with 30-day survival, transfers out of the health system or inpatient deaths). We did not have to account for left-censoring since our outcome of interest was HAPI not present on admission. We considered study exits due to discharge non-informative censoring; discharges of any type did not introduce selection bias since they would not affect HAPI risk in the remaining sample.

We used the STATA14 program *mestreg* with Weibull distribution and robust standard errors (Crowther, 2017). We chose robust standard errors because they are the most resistant to incorrect modeling assumptions.

Model Building

Our initial model included nine previously reported patient variables and twelve hospital candidate variables. Using stepwise backwards elimination, we removed hospital-level variables not meeting the statistical significance threshold of $P < .20$ ($n = 8$). We retained the patient-level variables employed in the previous model. The first resulting model included spline-transformed hospital variables for percent of patients with long-term care discharge, percent of patients with a high comorbidity burden plus percent of patients with a history of

Type 2 diabetes mellitus, and hospital patient mortality. Cross-validation of this first model in the derivation dataset across five equally sized partitions demonstrated substantial loss in model performance. After running a second step-wise backwards elimination process without the splines, we again retained hospital mortality and hospital percent of episodes with a history of diabetes. Cross-validation of the second model demonstrated good model fit (c-statistic = .792, Pearson product-moment correlation coefficient $R^2 = .0868$). Final validation of the model in the 30% validation dataset confirmed model fit (graphs omitted).

Results

Final Risk-Adjusted Model

Of the twenty-two initial hospital variables, we excluded ten from model building due to collinearity, and ten in model building, resulting in two final hospital variables (Figure 1). The final model had patient age, gender, COPS2, LAPS2 at admission, total Braden scale at admission, history of diabetes and history of stroke, admit category, and resuscitative code status at the patient level, while the hospital variables were hospital mortality rate, and hospital percent of patients with a history of diabetes.

Cohort Characteristics

Table 1 shows patient-level cohort characteristics by HAPI/non-HAPI episodes. Fewer women had a HAPI episode than a non-HAPI episode (43.5% vs. 53.4%). On average, patients with HAPI episode were older (71.3 years vs. 65.4 years), had a higher comorbidity burden (COPS2 78.8 vs. 48.5), higher severity of illness score at admission (LAPS2 93.3 vs. 59.6), lower Braden score at admission (15.4 vs. 18.7), higher length of stay (22.9 days vs. 4.5 days) and higher 30-day mortality (24.4% vs. 5.8%).

Intra-System Variation of Hospital-Level Variables

Table 2 describes the twelve candidate hospital variables including their respective degree of unadjusted variation across hospitals. We found a high coefficient of variation (standard deviation/mean >1.0) in hospital county population density (1.51), an indicator of rural vs. urban location, and percent of patients with a sepsis admission diagnoses (50.7). Ten variables had a low coefficient of variation ($CV = SD/mean < 1.0$). These results indicate that relatively little variation persisted across hospitals in the health system with respect to hospital occupancy ($CV = 0.22$), mean patient age ($CV = 0.03$), mean Braden score ($CV = 0.02$), percent of patients with high comorbidity ($CV = 0.10$), severity of illness at admission ($CV = 0.18$), history of diabetes ($CV = 0.11$), history of stroke ($CV = 0.14$), ICU stay in episode ($CV = 0.44$), discharge to long-term care ($CV = 0.26$), and patient mortality ($CV = 0.22$).

Hierarchical Survival Analysis of Hospital Variables

After adjustment for patient-level and hospital-level variables, the hazard for HAPI decreased by 4.8% for every 0.1% increase in a hospital's mean mortality ([6.3%, 2.6%], $P < .001$). The hazard for HAPI increased by 5% for every 1% increase in the proportion of patients with a history of Type 2 diabetes ([−0.4%, 10.0%], $P = .072$).

Model Impact on Hospital Variation of HAPI Risk

Compared to the patient-level model, the new model decreased unexplained hospital variation of HAPI risk by 35% (hospital-level variation 0.59 vs. 0.39). We utilized *coxme* code in R (Therneau, 2015) to calculate each hospital's individual effect of HAPI risk before and after the addition of the hospital variables. In the new model, the hospitals' HAPI risk rankings rearrange across the system, meaning that the order of low-to-high variation changes as the new model adjusts for the hospital variables. Figure 1 shows the reordering of hospital rankings: In the model without hospital variables, hospital IDs 30–35 had the top 5 highest facility effects. After adjustment for hospital variables, the top 5 hospital ID's were 29, 31, 32, 24, and 33. Figure 2 illustrates how the new model readjusts the hospital effects of HAPI risk across the 35 hospitals, including quite stark reductions in some hospitals as well as apparent risk reversal in others. A review of hospitals with such reversal suggested that these facilities had values that were substantially higher or lower than average for either hospital mortality or proportion of patients with diabetes.

Discussion

This large retrospective cohort study offers new insights into the field of HAPI risk adjustment and offers an important addition to translational nursing science and delivery science research. Our review of the literature suggests that the effect of hospital characteristics on HAPI risk has not been studied extensively. To our knowledge, this is the first study that evaluated the addition of a wide variety of hospital characteristics (other than nursing variables) to an existing HAPI risk model. Our results from this cohort study suggest that adjusting for hospital mortality and percent of patients with diabetes may reduce unexplained HAPI variation across hospitals. Organizational quality improvement activities and electronic clinical decision support rely on risk-adjustment. Without hospital-level risk adjustment, health care delivery system stakeholders may pay attention to the wrong outliers, i.e., they may allocate resources and implement programs that are not fine-tuned to their respective hospital characteristics.

Hospital Mortality

The observed association of hospital mortality with HAPI may be a function of the statistical methods used to model competing risks. In competing risk analysis, an individual may fail from one of several event types (here: HAPI or all-cause discharge). However, only the time to failure for the earliest event is observed (Dignam, Zhang, & Kocherginsky, 2012). Two approaches are generally used for competing risk analysis: cause-specific hazard function and the cumulative incidence function. The cause-specific hazard of a given event type reflects the rate per unit of time of the event (e.g., HAPI) among those having not failed from other events (i.e. all-cause discharge). The cumulative incidence of the event reflects the rate of the event as well as the influence of competing events (Dignam & Kocherginsky, 2008). We have used the cause-specific hazard in this analysis because it better allows for the study of inter-hospital variation with a mixed effects model. This approach censors cases that end in discharge, i.e. the patient is taken out of the risk set once the patient has left the hospital and measures HAPI among patients that remain hospitalized. Thus, the facility-level mortality rate may be capturing the lower HAPI rate that is expected from patients who die.

It is also plausible that mortality has an independent effect on HAPI since, on average; hospitals with a high mortality rate likely serve a sicker or frailer patient population that is not entirely measured with the patient variables. For example, hospitals serving such patient populations may provide more resources (wound care specialists) to care for such patient populations. This resource availability may then extend to the wider population of hospitalized patients. A systematic review of HAPI prevention strategies (Sullivan & Schoelles, 2013) noted that organizational HAPI reduction programs are often broadly implemented across settings.

Hospital Percentage of Diabetic Patients

The effect of a hospital's percent of episodes with diabetic patients was quite small and did not reach statistical significance in our model ($P = .072$). We performed sensitivity analysis by comparing the effect of the hospital diabetes variable in a model with and without the patient-level diabetes variable. The effect for the hospital diabetes variable did not change substantially (HR 1.05, [.996, 1.107], $P = .072$ and HR 1.05, [.997, 1.108], $P = .067$, respectively). This suggests that the hospital-level diabetes variable is independent of patient-level diabetes. The direction of the putative association for the hospital-level effect of percent of diabetic patients was reversed (i.e., we expected to be protective rather than a risk factor, Table 2).

Excluded Hospital Variables

Even though a lack of statistical significance does not prove absence of an association (Type 2 error), it was noteworthy that only two of the twelve candidate variables made a statistically significant contribution to the new model. For example, the lack of association of hospital occupancy (a hospital's mean bed count as a percent of maximum observed bed count) with HAPI risk was surprising. Prior evidence suggests that higher workload may be associated with lower HAPI risk (Cremasco, Wenzel, Zanei, & Whitaker, 2013), and results from this study did not produce evidence to the contrary. Associations of critical care utilization, long-term care discharges, or population density of the hospital's county, too, did not have a strong effect. The relatively low degree of variation of most of these variables across the health system (Table 2) might be one explanation. By the nature of its integrated structure, hospitals in the healthcare delivery system in this study appeared to be alike in many of its hospitals' characteristics.

Results in the Light of the Structure-Process-Outcomes (SPO) Model

Results of this study align with Donabedian's SPO framework. Accounting for hospital mortality appears to improve the measurement of HAPI risk in a large integrated healthcare delivery system. Not adjusting for hospital characteristics may distort the picture of HAPI risk because it assumes all hospitals are equal when in fact they are not. While we retained only two of the twenty-two hospital variables in the model and only included variables that showed a quantitative contribution, this study demonstrates that there are certain hospital characteristics that help explain HAPI rate variation across hospitals for the purposes of risk adjustment and quality measurement. It is known that targeted HAPI prevention strategies may have a net-positive return on investment, returning 61 cents for every dollar invested (Spetz, Brown, Aydin, & Donaldson, 2013). However, without a clear understanding of true

risk, interventions that aim to reduce HAPI may actually be wasteful. Consistent with the SPO framework, risk adjustment by hospital mortality seems to make HAPI risk measurement more reliable, informative, and useful for both clinicians and health system leaders.

Limitations

This study has several limitations. First, our findings cannot establish a direct causal role between the observed effects. Nevertheless, the associations we found are plausible, and model testing indicated robust performance using both cross-validation and split validation techniques.

A second limitation is the moderate sample size at the hospital level in our hierarchical model (35 hospitals). Even with nearly $\frac{3}{4}$ million patient episodes, the number of hospitals (and not the number of episodes) is the limiting factor when accounting for hospital characteristics. This restriction limited the number of variables that could demonstrate statistical significance. However, despite potential sample size limitations at the hospital level, this study is the largest investigation of the impact of hospital characteristics on intra-system variation of HAPI risk to our knowledge. The ability to pool data across organizational boundaries is still hindered by a variety of factors, including strict patient privacy regulations and lack of data interoperability (Linnen, 2016). These obstacles to “big data” nursing research are not unique to this study.

Third, the setting of this study is one of the largest integrated healthcare delivery systems in the United States. Decades of work in nursing care process standardization, quality improvement, and deploying innovation in professional nursing at Kaiser Permanente (Crawford, Corbett, & Zuniga, 2014; D’Alfonso, Zuniga, Weberg, & Orders, 2016; McCreary, 2010; Rondinelli, Ecker, Crawford, Seelinger, & Omery, 2012) have aimed to improve nurse-sensitive patient outcomes and decrease outcome variation. These efforts appear to be successful given that the health system is performing substantially better than the national average with a HAPI proportion of 2.3/1000 patients in this study compared to the 2014 national average of 30.9/1000 patients (Agency for Healthcare Research and Quality, 2016a). As previously discussed, Table 2 shows that intra-system variation for most hospital variables was small, suggesting that care within the system is likely more streamlined than it may be in other settings. Even though the research setting may limit generalizability, results from this study do apply to other integrated health systems of similar size and a similar degree of practice standardization.

Fourth, given that our study was limited to California hospitals, generalizability may be limited to settings with similar large metropolitan centers and strong economies (e.g., New York City or Washington, DC). While the study’s location may further limit generalizability, it is known that the health system is representative of California’s patient population at large (Koebnick et al., 2012).

Fifth, we did not verify the reliability of HAPI outcome measurement independently in this study. We deemed HAPI episodes documented in the sentinel event database to be a valid

and reliable measure of true HAPI episodes. Despite this limitation, prior evidence suggests that nurses can reliably and accurately recognize and stage pressure ulcers (Hart, Bergquist, Gajewski, & Dunton, 2006). In addition, manual chart reviews of HAPIs in the sentinel event database suggested that nurses tended to over-document a concern for HAPI. Thus, it is very likely that our outcome definition, at worst, resulted in overly conservative estimates of true HAPI risk.

Conclusion

We found that adding two hierarchical variables (hospital-level-mortality and percent of episodes with diabetic patients) decreased residual variation in HAPI incidence substantially. The magnitude of this effect – a 35% relative reduction – suggests that both the risk factors we identified as well as the methods we employed should be considered by health care delivery systems aiming to arrive at an unbiased comparison of HAPI risk across hospitals and to reduce HAPI rates. The remaining variation in HAPI risk between hospitals warrants further investigation. Independent factors that could be evaluated include characteristics of nursing staff (e.g., years in nursing, tenure at hospital, educational attainment), structural measures (e.g., bed surface type availability and utilization, specialty bed refresh cycle, linen type), and process measures (e.g., elapsed time from risk identification to specialty wound nurse referral, time from risk identification to specialty bed delivery). Future studies should also aim to combine large EMR datasets across organizational boundaries and consider using time-dependent transformation of variables (e.g., annual mortality vs average mortality).

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

We would like to thank Dr. Jim D'Alfonso, DNP, RN, Executive Director of the Kaiser Permanente Northern California Nurse Scholars Academy, for his administrative support, Dr. Tracy Lieu, MD, Director of the Kaiser Permanente Northern California Division of Research, for reviewing the manuscript, and Ms. Kathleen Daly and Mr. Fernando Barreda, Research Associates at the Kaiser Permanente Northern California Division of Research, for help with editing the manuscript. We thank Dr. Gretchen Summer-Gafford, PhD, RN, Director and Research Scientist at the Kaiser Permanente Northern California Nursing Research Community Benefit Program, Catherine Dower, JD, National Director of Nursing Research and Policy at Kaiser Permanente National Patient Care Services, and Dr. Dan Weberg, PhD, RN, Senior Director of Innovation and Leadership at National Patient Care Services, for their support and shared vision of nursing research and delivery science in our organization. The Kaiser Permanente Sidney Garfield Memorial Fund, the Kaiser Permanente Northern California Nurse Scholars Academy, Kaiser Foundation Hospitals, Inc., and The Permanente Medical Group, Inc. funded this study. As part of our agreement with the Sidney Garfield Memorial Fund, we made a commitment to disseminate our findings in articles such as this one. However, the Garfield Fund and its staff played no role in how we structured this article, nor did they or any of the other funders review or preapprove the manuscript submitted as part of the dissemination component. Dr. Vincent Liu was funded by NIGMS grant number K23GM112018.

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FIGURE 1.

Comparison of Hospital Rankings of HAPI^a Random Effects (Unexplained Variation) After Risk Adjustment in Two HAPI^a Models Using Hierarchical Survival Analysis in 35 Kaiser Permanente Hospitals in California

Note. X-axis: Hospital IDs rank-sorted by hospital random effects; Y-axis: Hospital random effect coefficients on the logit scale (unexplained hospital variation); In this graph, a negative tendency indicates below-average HAPI^a risk, A positive tendency indicates an above-average HAPI^a risk; ^a Hospital Acquired Pressure Injury

FIGURE 2.

Comparison of Hospital Random Effects (Unexplained Variation) Sorted By Hospital in Two HAPI^a Models Adjusting For Patient-Level Variables vs. Patient and Hospital-Level Variables

Note. X-axis: Hospital IDs sorted by hospital random effects in the model adjusting for patient-level variables; Y-axis: Hospital random effect coefficients on the logit scale (unexplained hospital variation); in this graph, Hospital IDs are sorted by lowest to highest hospital random effect ranking in the baseline model (black bars). The gray bars represent each hospital's random effect observed with the new model; ^a Hospital Acquired Pressure Injury

TABLE 1**Cohort Characteristics**

Variable	HAPI Hospitalization Episodes (n=1,661)		Non-HAPI Episodes (n=726,605)	
	N	% ^a	N	% ^a
Female	723	43.5	387,785	53.4
Ethnicity				
Caucasian	917	55.4	411,634	56.8
African-American	295	17.8	87,893	12.1
Hispanic	290	17.5	144,167	19.9
Asian	144	8.7	74,835	10.3
Other/Not reported	15	0.9	8,076	1.1
Hospital Acquired Pressure Injury stages				
I	164	9.9	-	-
II	697	42.0	-	-
III	43	2.6	-	-
IV	2	0.1	-	-
DTI ^b	626	37.7	-	-
Unstageable	129	7.8	-	-
Admission Type				
Emergency Department (ED), surgical	480	28.9	70,645	9.7
Non-ED surgical	242	14.6	162,824	22.4
ED medical	807	48.6	436,835	60.1
Non-ED medical	132	8.0	56,301	7.8
30-day Mortality ^c	405	24.4	42,333	5.8
	Mean	SD ^d	Mean	SD ^d
Age at admit (years)	71.3	13.9	65.4	17.3
Comorbidity score (COPS2) ^e	78.8	57.5	48.5	47.6
Severity of Illness score (LAPS2) ^f	93.3	50.2	59.6	39.7
Braden ^g score	15.4	3.3	18.7	2.9

Note.

^aPercentages were rounded to the first decimal and may not add to 100.00%^bDeep Tissue Injury^cPatient deaths within 30 days after admission including discharged patients^dStandard Deviation^eComorbidity Point Score version 2 (COPS2) measures a patient's comorbidity burden for the previous 12 months^fLaboratory-based acute Physiology Score (LAPS2) measures a patient's severity of illness using laboratory values and vital signs^gBraden Scale measures pressure injury risk using point scoring

TABLE 2**Unadjusted Variation of Hospital Variables Across 35 Hospitals**

Variable	Low	Mean	High	Coefficient of Variation ^a
Hospital occupancy ^b	-30.2%	-14.5%	-8.9%	0.22
Hospital county population density	101.2	1760.0	17132.7	1.51
Hospital mean patient age (years)	61.7	65.4	70.5	0.03
Patients with COPS2 ^c score 65	8.1%	12.0%	18.5%	0.10
Patients with LAPS2 ^d score 110	24.5%	29.6%	39.0%	0.18
Patients discharged to Long Term Care	6.8%	10.6%	20.1%	0.26
Patients with a history of diabetes	23.4%	37.2%	45.5%	0.11
Patients with a history of stroke	7.0%	9.8%	14.1%	0.14
Mean hospital Braden scale	18.0	18.7	19.2	0.02
Patient 30-day mortality ^e	1.8%	2.8%	4.0%	0.22
Patients with sepsis admission diagnosis ^f	0.0%	3.9%	33.6%	50.7
Patients with ICU stay	5.9%	13.4%	40.0%	0.44

Note. The above 12 variables remained after 10 variables were excluded after collinearity testing

^aCoefficient of Variation = SD/mean. A higher ratio indicates more variability in the data

^bMean monthly occupancy as % difference of highest observed monthly occupancy. Values are negative because they indicate the difference relative to highest observed occupancy.

^cCOPS2 is a measure of a patient's comorbidity burden for the 12 months preceding admission

^dLAPS2 is a measure of severity of illness and includes vital signs and laboratory values

^ePatient deaths within 30 days after admission including discharged patients

^fSepsis ICD-9 admission codes 995.91=Sepsis, 995.92=Severe Sepsis, 785.52=Septic Shock