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Title: Quantifying Pediatric Intensive Care Unit Staffing Levels at a Pediatric Academic Medical Center: A Mixed Methods Approach

Short Title: Data Driven Discovery of PICU Nurse Staffing

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Title

Improving Nurse Staffing Through Data Driven Discovery of PICU Nurse-to-Patient Assignment Rules: A Mixed-Methods Approach

Abstract

Aim: To improve nurse scheduling by identifying and quantifying patient-level and unit-level factors associated with nursing demand.

Background: In hospitals, nurse staffing schedules are commonly set based on coarse metrics such as annual average midnight census that do not account for seasonality, midday turnover, or patient acuity. Such schedules frequently require modification with last-minute adjustments to set appropriate staffing levels and are associated with nurse burnout, patient care delays, and higher costs.

Methods: Historical staffing schedules at a pediatric intensive care unit (PICU) were simulated based on rules derived from interviews with charge nurses. Multivariate regression was used to model the discrepancies between scheduled and actual staffing levels and to construct rules to reduce these discrepancies.

Results: Staff schedules underestimated actual nurse staffing levels by a median of 1.5 nurses per shift. Multivariate regression identified the primary factors accounting for this difference as patient turnover, age, and weight. New rules reduced the difference to a median of 0.07 nurses per shift.

Conclusion: Measurable, predictable indicators of patient acuity and historical trends may allow for nurse schedules that better match unit demand.

Implications for Nursing Management: Data driven methods may be used to better understand what drives unit demand and generate nurse schedules that require fewer last-minute adjustments.

Key words: Simulation, staffing ratios, pediatric intensive care, nurse staffing, burnout

Background

Appropriate nurse-to-patient ratios are associated with reduced morbidity and mortality in the inpatient setting, including reduction in rates of infections such as pneumonia and urinary tract infections, failure-to-rescue, and length of stay (Aiken et. al, 2002; Aiken et. al, 2014; Griffiths et. al, 2018; Griffiths et. al, 2019; Kane et. al, 2007; Needleman et. al, 2002; Needleman et. al, 2011; Needleman et. al, 2020; Shang et. al, 2019, Shekelle et. al, 2013). Lower nurse-to-patient ratios are associated with nurse burnout, job dissatisfaction, and intention to leave (Shin, Park, & Bae, 2018, Aiken et. al, 2002).

State governments have instituted minimum nurse-to-patient ratios. Findings on resultant changes in quality have been mixed. In California in 2004, minimum mandatory hospital nurse-to-patient staffing ratios were introduced, and while overall staffing levels increased, resulting changes in nursing-sensitive quality metrics, such as rates of failure-to-rescue, infections, falls, and development of pressure ulcers, were mixed (Cook et. al, 2012, Donadson et. al, 2005, Mark et. al, 2013). In Massachusetts, when similar legislation was enacted requiring use of a hospital-based acuity tool to determine 1:1 or 1:2 staffing ratios, no change in patient outcomes was observed (Commonwealth of Massachusetts; Law et al., 2018). Higher intensive care unit staffing is associated with reduced length of stay for ventilated patients (Falk & Wallin, 2016), but there is relatively little evidence of the effects of nurse staffing levels on patient outcomes within intensive care units (ICUs).

Part of the challenge of using crude nurse-to-patient ratios to determine minimum staffing levels is that they may not fully account for patient acuity and workload. For instance, additional nursing effort related to admissions and discharges throughout the day, known as "churn," may significantly increase nursing workload while the net nurse-to-patient ratio remains the same (Hughes et al., 2015). In the neonatal ICU (NICU) setting, increased nursing workload, a function both of staffing ratios and nurses' subjective assessment, may be associated with missed nursing care and poorer outcomes (Tubbs-Cooley et al., 2019). Both organizational and patient factors may explain some of the variation in nurse staffing (Tawfik et al., 2020). Evidence from the pediatric inpatient setting also suggests that missed nursing care, or nursing care that is delayed or not performed (Kalisch, 2006), may be associated with a poor work environment, including inadequate staffing levels (Lake et al., 2017).

In order to compensate for fluctuations in patient workload and meet mandated ratios, nurse managers call nurses in or send nurses home on short notice. To facilitate such adjustments, hospitals have to maintain flexible staffing arrangements that may include on-call staff or overtime to meet greater-than-expected patient demand and policies that allow them to call off staff. Schedules that are unpredictable or subject to frequent disruption are negatively associated with employee health and well-being (Schneider & Harknett, 2019). Furthermore, when workload is underestimated and nurses are called in at the last minute, hospitals incur overtime costs; when workload is overestimated, hospitals incur costs of paying for excess labor. Hospitals may be able to improve efficiency, employee satisfaction, and patient care by reducing the need for last-minute scheduling adjustments with data-driven scheduling that accounts for the factors that drive staffing demand.

When making a shift schedule weeks or months in advance, nurse managers often consider a set of fixed rules to determine the number of nurses that should be scheduled. On the day before or day of the shift, charge nurses use an additional set of rules to adjust the schedule to achieve the staffing level they deem appropriate for the unit. Such adjustments are not fully explained by strict nursing assignment ratios; they rely on complex factors based on the charge nurse's gestalt about the demands of the unit. We sought to uncover quantitative proxies for these factors.

At present, there is scant scientific literature regarding patient characteristics and conditions that dictate specific nurse staffing schemes in the pediatric intensive care unit (PICU) setting. The primary aim of this study was to identify the formal and informal patient-level and unit-level factors that nurse managers and charge nurses use to determine the scheduled and actual number of nurses for each shift. The secondary aim was to identify patient and hospital unit characteristics available through the electronic health record (EHR) that could be used to better estimate in advance the actual number of nurses needed for each shift. Our hypothesis is that the use of such data from the EHR could facilitate creating schedules that require fewer short-notice adjustments.

Methods

Setting

This study took place at a large academic medical center in California with a Level I trauma center with a transplant center, and extracorporeal membrane oxygenation (ECMO) capabilities. The hospital had 361 beds, and the PICU had 36 beds. This study was granted a quality improvement exemption by the Stanford University Institutional Review Board.

Interviews and Data Sources

This mixed-methods study took place in two parallel phases.

Phase 1 was a series of 30-60 minute semi-structured interviews with staff from the same hospital, including nursing staff, nursing management, medical staff, medical directors of units, hospital data analysts, and hospital administrators. Question domains included how staffing is conducted at the hospital, timeline for staffing decisions, ratios for various patient conditions, unit flow by seasonality/day of the week/time of day, and general operations of the unit and the hospital.

Phase 2 involved quantitative data analyses of historical staffing and patient data. We used nurse staffing data, specifically employee shift records, from the Kronos workforce management software database (Kronos Incorporated, Lowell, MA). Patient data including diagnoses, procedures, and demographics were derived from the hospital specific data provided to the Virtual Pediatric Systems (VPS) database. VPS is a registry database for critically ill children admitted to member Pediatric Intensive Care Units used for benchmarking, analysis, and quality improvement reporting across participating hospitals (Virtual Pediatric Systems LLC, 2020). Finally, financial data which recorded the number of full time equivalent (FTE) nurses per month was converted to an expected number of nurses per shift based on operational budgets.

The study period was from January 2018 through May 2019 (17 months). Notably, there were sporadic spikes in nurse counts, which occasionally jumped more than 100% in an hour. These spikes were attributed to nurse training or other staff functions where staff were not performing clinical duties. To account for this anomalous data, any time the number of nurses exceeded 50% of the rolling daily median number of nurses in the PICU, the number of nurses was replaced with the rolling daily median.

Computer Simulation Analysis

Rules for shift-specific staffing levels were derived from interviews with nursing and medical leadership. Managers were interviewed to determine the number of nurses needed for each patient based on having had a procedure with a mandated nursing ratio, as a safety buffer based on the overall patient census, and to serve as managers and charge or float nurses. For each shift, the staffing level was estimated as scheduled in advance based on the budget, after changes made close to the day of the shift based on unit-specific rules, and with a hybrid rules- and regression-based model.

The budget-based estimate produced a static monthly number of nurses per shift defined as the number of budgeted full time equivalents (FTEs) per month divided by the number of shifts. The rules-based estimate was produced with simulation of the per-shift number of nurses by using the rules to translate historical data extracted from the EHR on the number of patients in the unit that met each of the interview-derived staffing criteria as well as the total number of patients in the unit. Estimates were averaged over four-hour windows to eliminate noise in the data.

To evaluate their accuracy, we compared the budget-based and rules-based staffing estimates to actual historical staffing levels. The metric used was the median difference between the number of nurses estimated and the actual number of nurses over a four-hour shift block. Subgroup analyses were performed for day shifts (0700-1900), night shifts (1900-0700), weekdays, and weekends. We classified a shift as requiring adjustment by the charge nurse if the actual number of nurses working differed by more than 2 from the estimated number. The number of shifts requiring adjustment was calculated for each staffing strategy.

To identify patient-level and unit-level characteristics associated with the differences between the estimated and actual staffing data, multivariate regression analysis was performed. Input features were hourly counts of patient-level features, including counts of the number of patients in the PICU with specific diagnoses classes, demographic information, and procedures. Also included in the analysis were unit-level features such as the number of admissions and discharges in retrospective windows ranging from 1 to 24 hours, day of the week characteristics (weekday, weekend, or holiday), and the number of patients in other units in the hospital. There were a total of 351 input features. The response variable was the error between the estimated number of nurses and historical staffing. The 10 largest regression coefficients along with 95% confidence intervals were reported. This hybrid regression model was trained to account for the interview-derived rules and EHR factors identified by the multivariate regression model. Its output was compared against the two aforementioned strategies. In addition, three separate exploratory multivariate regression analyses were also performed on specific feature types derived from VPS: procedures that patients were undergoing, diagnoses groups, and demographic information.

All data preparation and simulation was performed in R 4.0.2 (R Foundation for Statistical Computing, Vienna, Austria).

Results

Patient and Unit Characteristics

There were 2,796 PICU admissions during the study period from 2,112 unique patients (Table 1). The median patient census across all shifts during the study period was 23 patients (interquartile range (IQR), 20, 26), with 114 unique nurses working 20,121 shifts. The most common diagnoses were neurological (1453/2796, 52.0%) and respiratory (1426/2796, 51.0%) related. The median number of shifts worked by each nurse per month was 13.0 (IQR, 11.0, 15.0). The median hourly nurse-to-patient ratio was 1.35 (IQR, 1.16, 1.60).

Interview-Derived Rules

A total of 30 interviews were performed with stakeholders. Nursing management reported that there were several specific patient characteristics and procedures that resulted in deviations from the usual legally mandated 1:2 nurse-to-patient ratio (Table 2). For instance, patients on extracorporeal membrane oxygenation (ECMO) and patients experiencing acute decompensation required a nurse-to-patient ratio of 2:1. Patients on continuous renal replacement therapy, those who were intubated or on mechanical ventilation, patients with high acuity treatment (such as intravenous blood pressure medication) and patients with high psychosocial needs (such as intellectual disability) required 1:1 staffing. All other patients fell into the category of 1:2 staffing, such as stable trauma patients or patients with diabetic ketoacidosis (DKA). Additionally, buffer staff, including the unit charge nurse, were available to assist as needed, for example in case of cardiac arrests or unplanned admissions, and were allocated to the unit based on patient census. All of these procedures were available as discrete fields in VPS with the exception of defining acute patient decompensation, high acuity medications, and high psychosocial needs.

Interviews revealed that day-of shift staffing was conducted in the following manner. Approximately 3-5 hours prior to the start of each shift, the charge nurse would verify that the nurses for the oncoming shift were both adequate in number and specialized skills (e.g. ECMO) for the patients on the unit. Adjustments could be made through multiple mechanisms, such as utilizing on-call staff, float pool staff, or trading staff with the cardiovascular ICU. Through this last adjustment mechanism, management could ensure sufficient nurse staffing by the start of the shift to meet the acuity and needs of patients on the unit, regardless of projections when the schedule was set. Importantly, all of these staffing adjustments were documented in Kronos, allowing for retrospective analysis.

Additionally, nurses noted several other situations that would demand additional nurse time, including high patient churn, large surgical case volumes, and unanticipated patient events on the unit. However, no specific staffing rules were in place to adjust for these events; rather, charge nurses would use their judgement to decide what staffing changes needed to be made in order to meet the needs of the PICU.

Computer Simulation Analysis

When the results of simulated nurse staffing were compared to actual staffing, large discrepancies were noted. Using a budgeted staffing model, the monthly estimate of nurse staffing underestimated the number of nurses on a shift by 0.87 nurses per shift (IQR, -2.90, 1.01), meeting criteria for adjustment 48.4% of the time (Figure 1). Simulating interview-derived rules underestimated the number of nurses that worked a shift by a median of 1.5 nurses per shift (IQR, -4.0,1.5) meeting criteria for adjustment 61.9% of the time.

This discrepancy remained when examining specific subsets of shifts (Figure 2). Simulations for weekend shifts were the closest to actual staffing levels for both the budget staffing model (median underestimate of 0.65 nurses per shift (IQR, -2.49, 1.09)), and interview-derived rules model (median underestimate of 0.75 nurses per shift (IQR, -3.15, 1.75)). The largest discrepancy was noted for day shifts, with a median underestimate of 1.75 nurses per shift (IQR, -4.12, 1.00) and 0.99 nurses per shift (IQR, -3.42, 0.82) for the interview-derived rules model and budgeted staffing model, respectively.

Regression Analysis

The hybrid regression model overestimated the number of nurses per shift by 0.074 nurses (IQR, -1.19, 1.26), meeting the criteria for adjustment only 27.5% of the time (Figure 1). Results were very similar results across all shift subgroups (Figure 2).

The ten largest regression coefficients that influenced the observed error between simulation and historical staffing are plotted in Figure 3. Nine of the ten variables that were most associated with errors between simulations and historical staffing were variables associated with patient churn as quantified the number of patients admitted and discharged from the PICU within a given look-back window. The factor with the strongest association was the cumulative number of patients admitted in the past 14 hours with a regression coefficient of 3.579 (95% CI, 1.583, 5.575).

Notably, patients who weighed more and older patients (18-19 years old) tended to contribute more to the error observed (Figure 4); this was occasionally brought up in interviews as requiring more staffing resources, but no formalized staffing rules had been established. Both procedures (electroencephalography) and diagnoses (neurologic complications) that were associated with neurological impairment increased simulation error (Figure 4).

Discussion

In a pediatric intensive care unit in a pediatric academic medical center over the course of 17 months, interview-derived rules (staffing rules derived from nursing management) underestimated the actual number of nurses required by a median of 1.5 nurses per shift across weekend, weekday, day, and night shifts. Multivariate regression identified patient turnover, patient age, and patient weight as the factors most strongly associated with differences between interview-derived rules and actual staffing levels. Staffing levels set using a hybrid regression model demonstrated improved concordance with historical staffing counts, overestimating staffing needs by just 0.074 nurses per shift. In the regression analysis, we find evidence for a number of changes that can improve staffing schedules based on churn metrics, although no formal ratio can capture this complexity. Multivariate regression analysis is able to improve the goodness of fit of the simulated staffing rules.

This study demonstrates that applying interview-derived rules retrospectively to nurse staffing and then analyzing the difference from the actual staffing levels may allow nurse managers to identify patient- and unit-level characteristics that frontline nurse staff account for in order to set staffing levels. If this kind of analysis is performed at other institutions with similar input variables, potential findings might include other procedures that frequently require increased nurse workloads or days of the week when nurse staffing seems to be underestimated. These kinds of data-driven insights can be particularly important in terms of patient safety as nurse managers can pre-emptively intervene and alter staffing rules that reflect the current front-line reality of staffing, providing more transparency and guidance for charge nurses.

This work overlaps with a recent systematic review to identify nurse staffing methodologies, which found six mechanisms for staffing: professional judgement, benchmarking, volume-based or census-based staffing, patient prototyping, multifactorial indicator approaches, and timed-task approaches (Griffiths et al., 2020). The review also discusses that while better staffing has been shown to improve patient outcomes, "optimal" staffing is still an elusive construct. It also shows one way in which large EHR datasets may be used to optimize healthcare operations in general, and nurse staffing in particular (Spetz, 2020). This study provides evidence that combining professional judgement, census-based staffing, timed-task approaches, and multifactorial indicators, provides better estimates of retrospective staffing requirements compared to any one of these methods alone.

Limitations

There are some limitations to this study. It was assumed that all recorded PICU nurse shifts were spent performing patient care in the ICU, and that outliers, truncated as described in the methods section, were not representative of the true ICU staffing time. Second, the validity of conducting simulation and regression analyses over a 17 month time period is based on the assumption that hospital dynamics do not change over this timeframe. While this was true for the data used in this study, it must be kept in mind if the methods used here are applied to other hospital units. Third, for an insightful regression analysis, it is important to include all relevant drivers of staffing, since data such as certain patient characteristics may not be available through VPS (e.g. high acuity medications, acute decompensation); adding in these factors will likely further improve results shown in this study. Fourth, regarding generalizability, this study was conducted in a single academic pediatric hospital which may limit applicability of the findings to other settings and patient populations.

Future Work

Because VPS is a common data model for PICUs across the country, similar kinds of analysis could be performed using similar types of inputs and outputs described in this study. Building on this analysis, future studies should endeavor to identify more granular patient characteristics that are available through the EHR that may modify baseline staffing ratios due to variations in nursing workload. These characteristics, including medications and vital signs, could also be used to better model estimations of staffing needs on a given unit.

Additionally, a natural extension to this study would be to create a forecasting model, not just for each shift, but also for weeks or even months in advance. For example, accounting for seasonality factors and conducting further analytics based on patient data with time series analysis and machine learning techniques including deep neural networks can be used to yield better forecasts. Time series analysis would be particularly conducive in accounting for patient churn. Similar methods (DeRienzo et al., 2017; McCoy et al., 2018) have previously been used in other medical settings. Even with less granular predictions, these analyses will significantly aid shift-level staffing and also provide data-driven support for investing in hiring and training activities well in advance, instead of basing this investment only on known patient demand.

Conclusion

While patient census and unit workload may be volatile, this study indicates that there are means of improving estimates of staffing needs based on historical staffing patterns, expert opinion, and EHR variables, potentially contributing to improved staff satisfaction and consequent hospital outcomes. Institutional and governmental policy around staffing ratios should not only account for patient census, but also patient acuity and unit level factors such as patient churn. Such data-driven considerations may prove valuable for nurse workforce planning as institutions invest in increasing or decreasing the volumes of patients associated with particular clinical programs, e.g., increasing certain types of surgical volumes. Identifying patient characteristics from nursing managers and EHR data may help codify how much nursing care is required for certain patients. This may help hospitals take a data-driven approach to making more accurate prospective predictions for how to predict unit staffing needs based on patient census, patient acuity, and the overall environment of the unit.

Implications for Nursing Management

Using the methods in this paper, nursing management will be able to identify and quantify pertinent factors that contribute to nurse staffing, which when taken into account, allows charge nurses and administrators to more accurately plan for staffing levels in future shifts.

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Characteristic	Value
Sex, n (%)	
Male	1538 (55.0)
Female	1258 (45.0)
Age upon admission, median (IQR), years	5.75 (1.57, 13.40)
Weight, median (IQR), kg	18.9 (10.5, 44.3)
Race, n (%)	
American Indian or Alaska Native	9 (0.3)
Asian	452 (16.2)
Black or African American	86 (3.1)
Hispanic or Latino	995 (35.6)
Native Hawaiian or Pacific Islander	34 (1.2)
Other/Mixed	97 (3.5)
Unspecified	207 (7.4)
White	916 (32.8)
Patient Origin, n (%)	
Another Hospital ED	570 (20.4)
Another Hospital ICU	89 (3.2)
ED	479 (17.1)
General Care Floor	459 (16.4)
Operating Room	947 (33.9)
Other	252 (9.0)
Trauma, n (%)	
Yes	133 (4.8)
No	2663 (95.2)
Disposition, n (%)	
Another ICU in Current Hospital	35 (1.3)
General Care Floor	1863 (66.6)
Home	773 (27.6)
Morgue	36 (1.3)
Transitional Care/ SNF	28 (1.0)
Other	61 (2.2)
Diagnosis Categories, n (%)	
Cardiovascular	711 (25.4)
Gastrointestinal	554 (19.8)
Genetic	358 (12.8)
Hematologic	471 (16.8)

Infectious Injury/Poisoning Metabolic Neurologic Oncologic Respiratory	635 (22.7) 378 (13.5) 499 (17.8) 1453 (52.0) 377 (13.5) 1426 (51.0)
Length of Stay, median (IQR), days	1.59 (0.916, 3.54)
Hourly patient census, median (IQR)	23.0 (20.0, 26.0)
Hourly nurse census, median (IQR)	16.0 (14.0, 19.0)
Hourly nurse-to-patient ratio, median (IQR)	1.35 (1.16, 1.60)
Number of Unique Nurses, n	114
Shifts per Nurse per Month, median (IQR)	13.0 (11.0, 15.0)

Table 1. Patient and unit characteristics. ED: Emergency Department, SNF: Skilled Nursing Facility; ICU: intensive care unit, IQR: interquartile range.

Procedure-based rules	**Nurse-to-patient ratio**
ECMO	2:1
Acute Decompensation	2:1
Continuous Renal Replacement Therapy	1:1
Intubated/ventilated	1:1
Outside Transfers	1:1
High Acuity (IV BP meds etc.)	1:1
High Psychosocial Need	1:1
All others (DKA, trauma, etc.)	1:2
Census-based rules	**Additional nurses**
0-17 patients	2
18-23 patients	3
24+ patients	4

Table 2. Interview-derived rules based on procedures and patient census

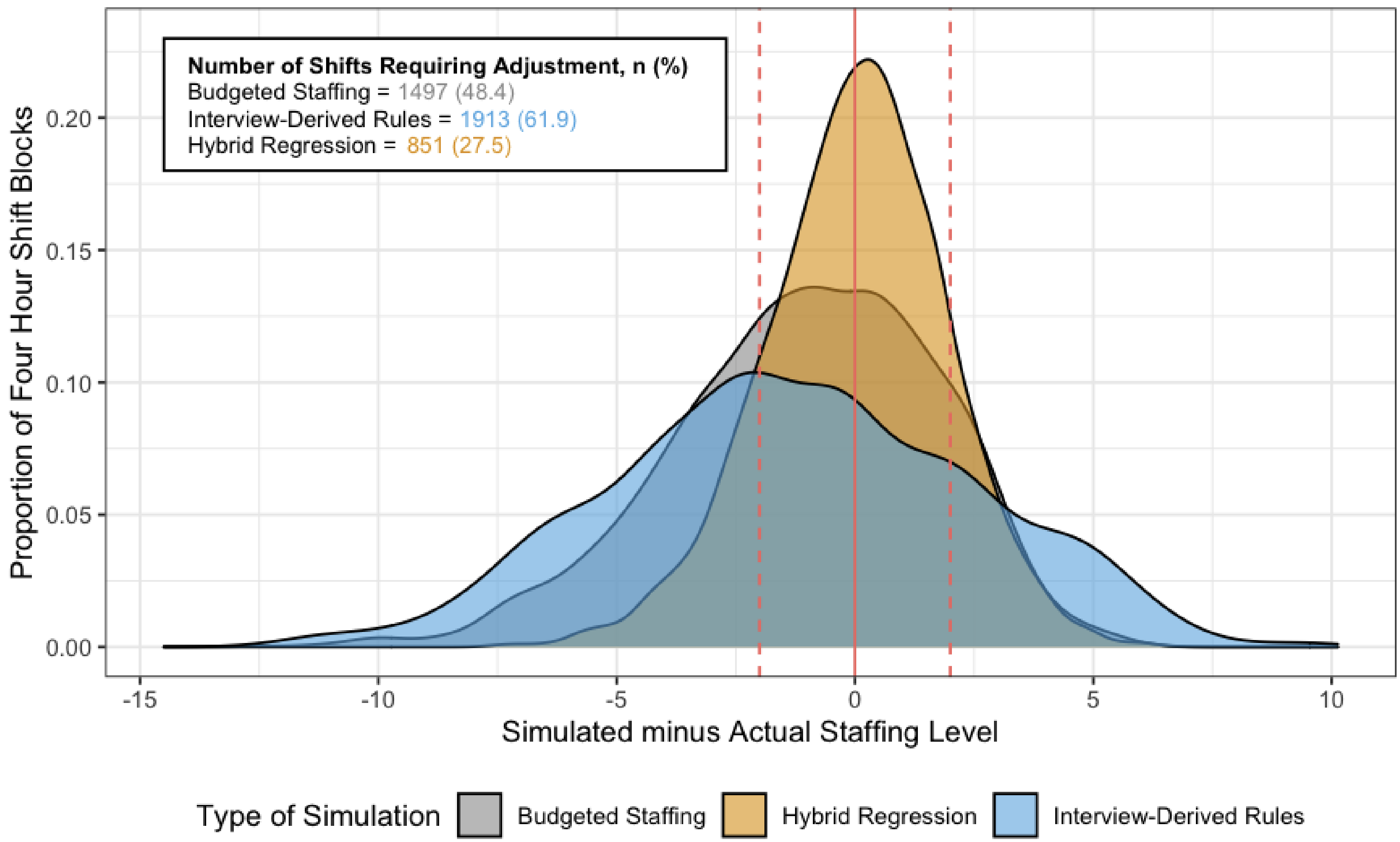
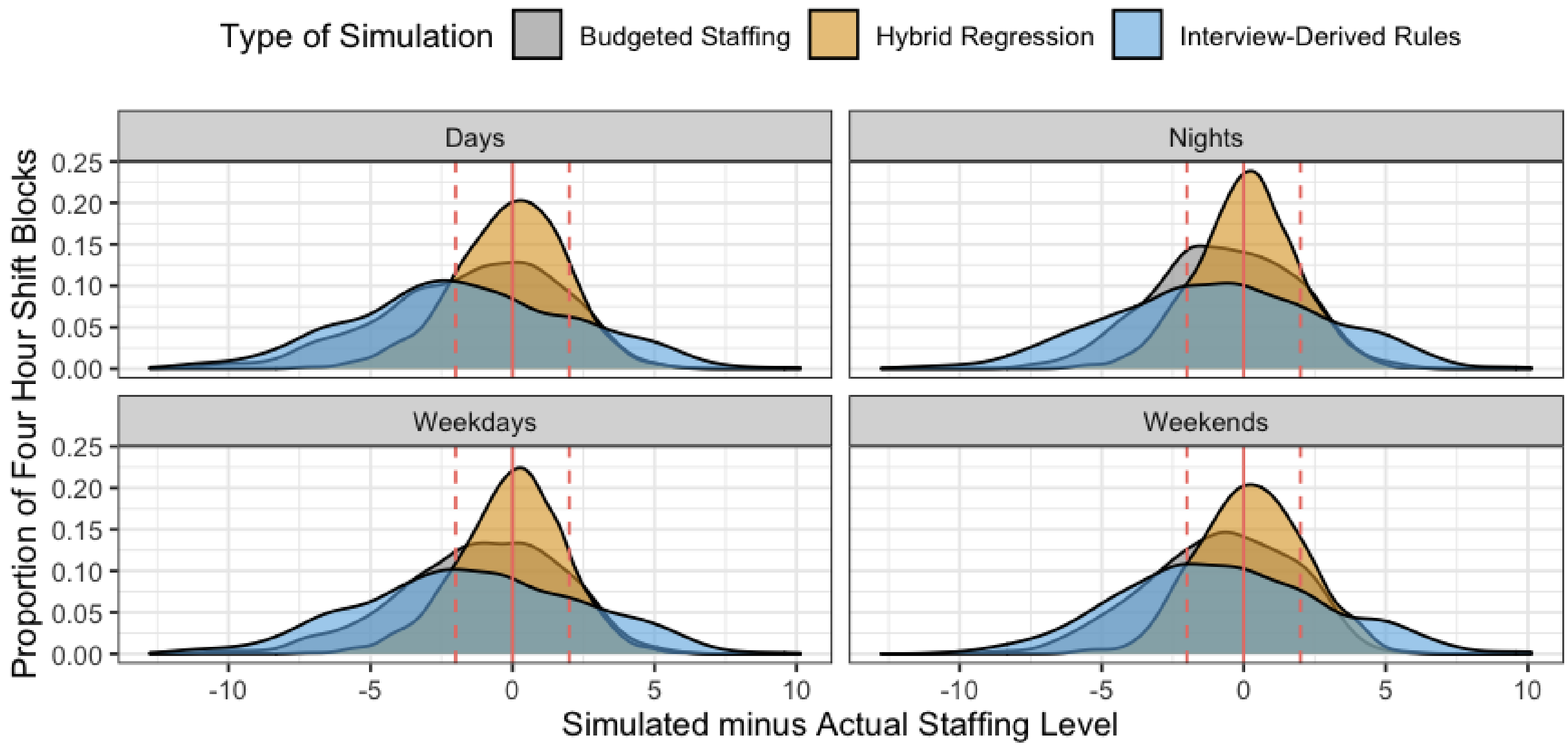


Figure 1. Differences between simulated and actual staffing levels from January 2018 to May 2019. The number of nurses averaged over four-hour shift blocks. Red dotted lines indicate +/-2 nurses, the level beyond which adjustment is considered required.



Type of Simulation	Days	Nights	Weekdays	Weekends
Budgeted Staffing	800 (51.8)	697 (45.1)	1287 (48.6)	210 (47.3)
Interview-Derived Rules	1009 (65.3)	904 (58.5)	1656 (62.6)	257 (57.9)
Hybrid Regression	446 (28.9)	405 (26.2)	722 (27.3)	129 (29.0)

Figure 2. Difference between simulated and actual staffing levels, segmented by day shifts, night shifts, weekend shifts, and weekday shifts. Data from January 2018 to May 2019. The number of nurses averaged over four-hour shift blocks. Red dotted lines indicate +/- 2 nurses, the level beyond which adjustment is considered required.

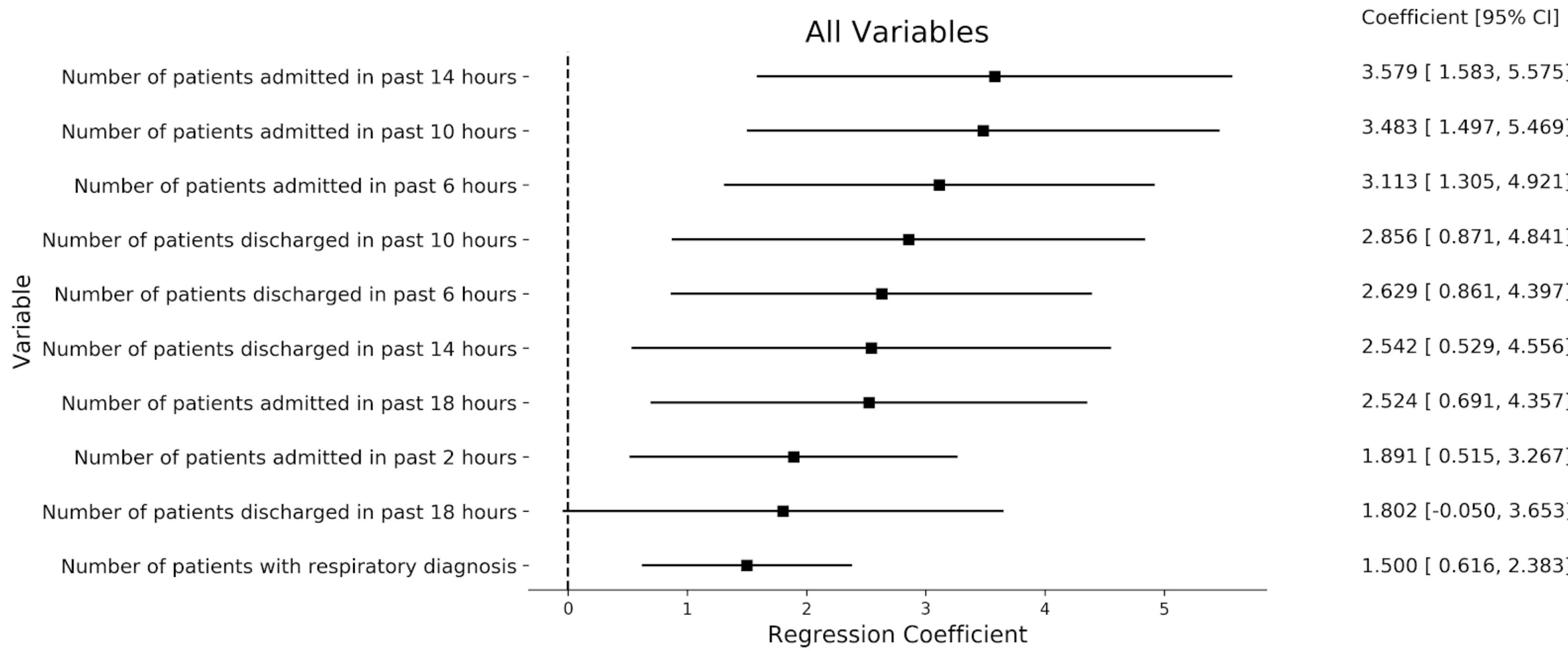


Figure 3. Top 10 predictive factors of staffing discrepancy as identified by regression analysis. Note that 9 of the top 10 factors all relate to patient churn. Error bars represent 95% confidence intervals (CI).

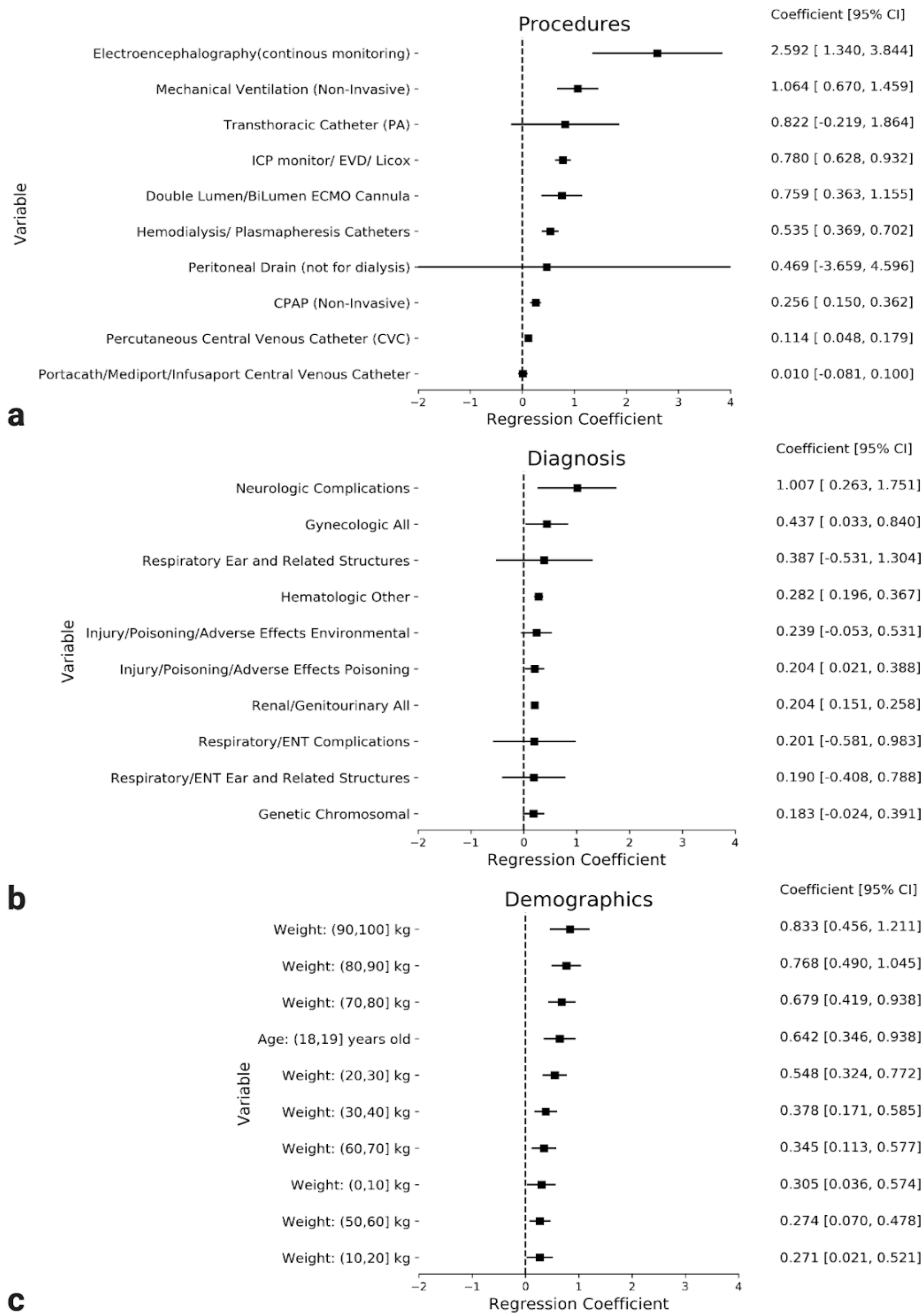


Figure 4. Regression analysis for three feature types: (a) procedures, (b) diagnoses, and (c) demographics. Error bars show 95% confidence intervals (CI).