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The Development And Implementation Of A Forecasting Model For Inpatient Nurse Scheduling

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Abstract

Objective: This study was designed to develop a model for predicting nurse scheduling needs in a hospital unit based on historical patient census and nurse staffing requirements.

Background: Many hospitals use outdated non-data driven methods for nurse scheduling.

Methods: Historical nurse scheduling and staffing datasets for 2015, 2016, and 2017 from a 33-bed surgical unit in an inner-city urban hospital in Portland, Oregon, were used to build a predictive model for nurse scheduling needs.

Results: The patient census for 2017 was three patients higher than the two previous years and showed a variation in the day of the week, with a consistent weekly trend of more nurses needed at the beginning of the week and fewer needed during the weekend.

Conclusion: Based on model predictions, nurse scheduling in this unit should vary by day of the week, which has not historically been done.

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Background

The Nurse Scheduling Problem

The staggering cost of healthcare in the United States is at an all-time high. Healthcare expenditures are 17% of the gross domestic product (GDP), with a forecasted GDP increase to 20% by 2020 (1). Thirty percent of healthcare expenditures are attributed to hospital costs, and more than half of that cost is associated with labor, equating to an annual expense of $300 billion (2). Additional scrutiny of labor-management is often imposed on the profession of nursing since nursing labor costs typically account for a large portion of a hospital's budget and can even be upwards of 50% of the total budget (3,4). Although this expensive problem is commonly known among healthcare leaders, the organizational importance of controlling nursing labor costs through the complex task of nurse scheduling continues to be undervalued and under-rewarded (5). In fact, many hospital nurse leaders are expected to create optimal nursing schedules without sufficient organizational support, incentives, tools, technology, or knowledge to address the nurse scheduling problem (NSP) (6,7).

The Nurse Scheduling Problem in the Practice Environment

The NSP is a "complex combinational optimization problem that can be modeled mathematically" (5; p. 801). The term is used in academic literature for the managerial and organizational complexities associated with developing a hospital inpatient nursing schedule. The optimal schedule ensures "the assignment of the right people to the right task, to the right time and to the right place" (5; p. 801). Thus, it involves multifaceted operative management that does not operate from a simple supply-and-demand economic model. In short, there is no easy formula for solving the NSP (7), nor does a gold standard of standardized scheduling methods exist. Rather there have arisen multiple suggestions and philosophies on how to achieve appropriate nurse scheduling (8,9).

In the building phase of the scheduling process, nurse leaders manually consider a variety of weighted variables, including federal and state regulations, patient characteristics, nurse characteristics, shift length, technology, cost, supply, and theoretical models of staffing (9). Once the schedule has been built, many such leaders spend a significant amount of administrative time managing and maintaining the published schedule. The majority of that time is spent reworking and changing the schedule to accommodate for expected and unexpected variables such as emergency leave, sickness, study days, worked overtime, and fluctuations in bed occupancy (10).

However, regardless of the countless hours and well-meaning intentions of nurse leaders to make and maintain a good schedule, misalignment continues between the supply and availability of nursing personnel and the actual demand, thus illuminating the inadequacies of current scheduling procedures and the lack of accurate forecasting methods. In fact, many organizations still employ rudimentary approaches for nurse scheduling and staffing, which are insufficient in meeting the present—and future—nurse staffing demands (7,11). For example, nurse leaders commonly experience the phenomenon known as "the flaws of averages," a planning process that uses a single averaged number representing patient census to determine daily resource needs. That process typically leads to gross over- and understaffing (7).

The negative effects of insufficient nurse staffing associated with adverse patient outcomes, low nurse retention rates, unhealthy work environment, and high nurse leader workload and burnout are overwhelming (12). Basic staffing and scheduling methods of the past are not meeting the complex demands of the present and future staffing environment for nursing.

The complicated environment of healthcare requires a more sophisticated supply-and-demand simulation modeling to predict and plan for nurse scheduling and staffing needs. Planning methods must evolve into more advanced forecasting modeling techniques that support nurse leaders in meeting the increasing demands of the NSP (7).

Closing the NSP Research-to-Practice Gap

Nurse Scheduling Problem – Gaps in Practice

The disciplines of computer science, management science, and operations research have produced a robust body of research applicable specifically to the NSP. That research has proposed solutions such as optimization methods, algorithms, forecasting techniques, and decision-support systems, each with the potential to provide significant cost-savings and quality impact (11). However, even with the robust body of academic research on the NSP, a substantial gap exists in translating that research into practice on a global scale when it comes to using demand modeling tools and techniques for nurse scheduling (7, 13). Practice gaps often exist for a variety of reasons, including a limited collaboration between the researcher and the practice environment, research that is too narrowly focused, limited relations between the large scheduling vendors and academic partners, technological support issues, nursing acceptance issues, and the inability of models to incorporate self-scheduling techniques (11, 13).

Additional gaps may exist because research conducted in disciplines other than nursing has not appeared in nursing journals, thus, creating a lost opportunity to inform and influence the nursing audience to change practice (11). The research also frequently lacks discussion on the practical use and implementation of the findings, focusing instead on the model build and notation, in language unfamiliar, and perhaps intimidating for many nurse leaders. Some NSP forecasting models are also highly constrained due to the multifaceted nature of the NSP, thereby reducing the generalizability of a model from one practice environment to another (5, 14).

Closing the research-to-practice gap for the NSP is important for several reasons. The non-data-driven management methodologies are likely to increase overall healthcare costs due to mismanagement of expensive nursing personnel resources (7). Developing a schedule that is robust and aligns with staffing resources to include skill mix, nurse preference, and cost requires adequate decision support infrastructure and sufficient data to avoid chance or guesswork allocation of resources (15). One recommended technique to bridge the gap between research and practice is to publish academic research in nursing journals by nurses or in partnership with nurses (11). Similarly, nurse scheduling models should be developed by nurses—or in partnership with nurses—and tested through implementation with results published in a wide variety of journals, including nurse-management journals. Broad publication, outside of the discipline of forecasting, can help distribute new knowledge to those who can directly impact the NSP (11).

Theoretical Framework: Demand Modeling

In 2004, Ernst et al. deconstructed the NSP into six modules, proposing that the tasks could be solved and implemented sequentially or combined depending on the build of the nursing schedule (14). Those six modules include demand modeling, day off scheduling, shift scheduling, line of work construction, task assignment, and staff assignment. The first step, *demand modeling*, translates predicted patterns of incidents to determine the demand for staff and is the focus of our nurse scheduling model. Incidents can be different occurrences that impact the scheduling environment, such as sick calls, vacations, patient census, and shift specification of staff levels. Often these aspects of the NSP are not solved concurrently because of the computational complexity but is instead evaluated in several steps to align with manageability and the business practices of the organization. Consequently, the step of demand modeling to predict patterns and forecast schedule needs is frequently evaluated and solved as a separate module (5, 14).

The demand modeling phase presents a need to "translate incident data to a demand for staff, and a method for forecasting incidents" (14; p. 6). In the hospital setting, the number of nurses needed is related to the number of patients and organizational or state regulations concerning nurse-to-patient ratios. Different approaches exist for forecasting the distribution of incident data for staff demand over a planning horizon. Those approaches include simple averaging, exponential smoothing, regression, and seasonal and nonseasonal autoregressive integrated moving average (ARIMA) models (14). Therefore, considering the existing research-to-practice gap, the existence of recommended techniques to close the practice gap, and the trending popularity of big data concepts in the healthcare environment, now is an ideal time to work on developing and implementing a nurse scheduling model for the demand modeling phase of the NSP (16).

Aims

In keeping with the theoretical framework of demand modeling, the objective of this study was to contribute to the goal of closing the practice-to-research gap by developing a nurse scheduling forecasting model to predict the total number of dayshift nurses needed during a defined period and implement the model predictions into a practice environment.

Methods

Data were obtained from an inner-city urban hospital located in Portland, Oregon. Nurse staffing, scheduling, and patient census data for a 33-bed surgical specialties unit were included. The surgical specialties unit provides care to adult and geriatric surgical patients related to neurology, orthopedics, podiatry, urology, bariatric, and general surgery 24/7 year-round. No identifiable patient or employee information was included.

Data Sources and Exploratory Analysis

Accumulated data from 2015, 2016, and 2017 for daily nurse scheduling and staffing for the 12-hour dayshift (0700-1900), a total of 896 observations per variable, were used for model build and validation. The 12-hour dayshift data included both the charge nurse and direct care nurses and was evaluated as the total number of dayshift nurses needed for each day. The other variable for the model was the daily patient census at 0300. Exploratory analysis of the data revealed no seasonal trend but a consistent pattern of weekly variation.

Model Theory and Design

Initial research and development indicated that an ARIMA type of model might work for modeling the times series nursing data. However, because there was no seasonal year-over-year trend, the ability to forecast was limited. Instead, linear regression was used to predict the impact of the number of nurses as a function of the patient census. Therefore, the bivariate linear regression model was estimated and resulted in the following:

$$Number\ of\ nurses\ needed = 2.96 + 0.168\ (Census\ count)$$

A one-person increase in the census requires a 0.168 increase or addition in nursing staff, which was statistically significant at $p<.01$. The regression demonstrated an R-squared of .36.

Once the nurse-to-census relationship was established, a census forecast was required to make the nurse-needed projection for a six-week scheduling period. Again, the census did not exhibit any seasonal trend and was driven by exogenous variables that were not available for modeling purposes. Therefore, the forecasted census was not modeled. Instead, a simple average of the previous time period of the 0300 census was used. The census forecast was created by taking the average of the last two years of that same six-week schedule period and shifting the date to align by day of the week, resulting in the following:

$$Census\ forecast = \left(\frac{\left(2015_{date\ day\ of\ week} + 2016_{date\ by\ day\ of\ week}\right)}{2} + 3\right)$$

Three units were added to the census because on average, the patient census for 2017 was three patients higher than for the two previous years. Average daily patient census at 0300 for both 2015 and 2016 was 23 and predicted patient census for 2017 was 26.

Additionally, the data showed a variation in the day of the week for the nurse-needed, with a consistent weekly trend of more nurses needed Tuesday through Friday and fewer nurses needed Saturday through Monday. Figure 1 demonstrates the frequency of nurses needed by day of the week for 2015 and 2016. For example, on Tuesdays 8 nurses were needed for the day shift 83 times and 4 nurses were needed only 5 times.

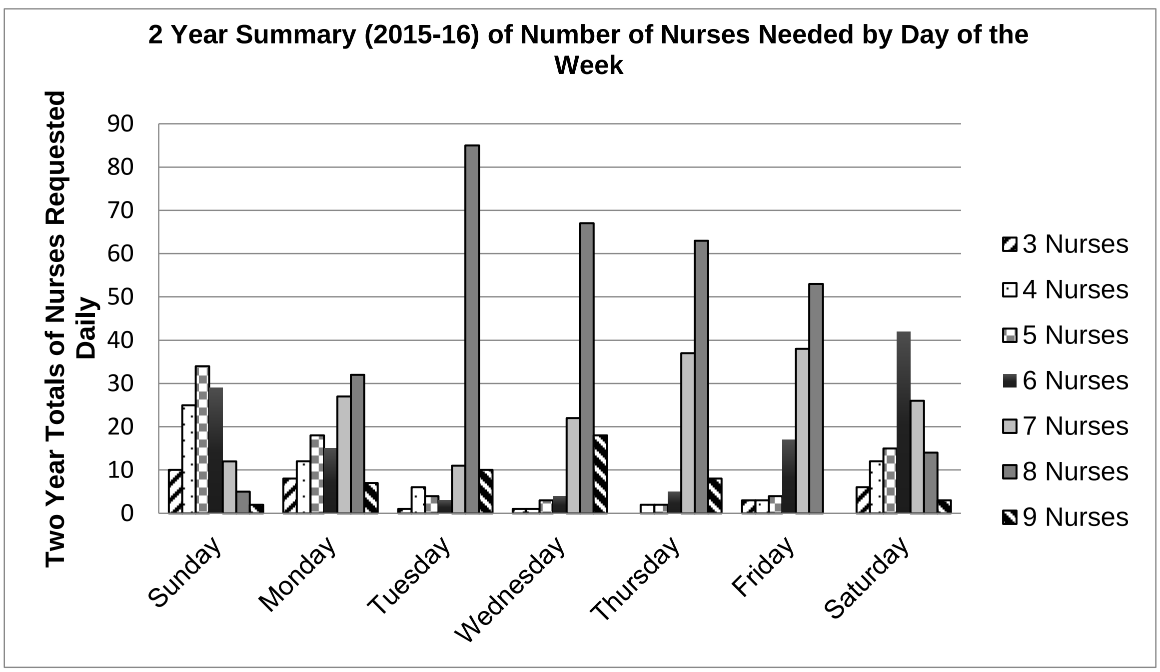

Figure 1.

Implementation

A six-week scheduling cycle was used for the testing period of November 12, 2017 to December 23, 2017. Eight weeks before the beginning of the test period, the nurse scheduling needs for the day shift were adjusted in the electronic scheduling system to match the predicted needs generated from the model. The implementation of model predictions was made before the employee self-scheduling period. After predictions were implemented, unit scheduling practices of employee self-scheduling and managerial balancing resumed for the creation and publishing of the six-week schedule.

Results

After the nurse schedule model build and predictions were completed, analysis of the predictions was compared to past scheduling practices, revealing that current and past scheduling practices were consistently underestimating by 1.2 nurses the number of 12-hour dayshift nurses needed. There were wide deviations of nurse schedule needs ranging from underpredicting by 4 nurses and overpredicting by 5 nurses per shift as seen in Figure 2. The study’s forecast model resulted in more accurate scheduling predictions by reducing the wide variations associated with past scheduling practices.

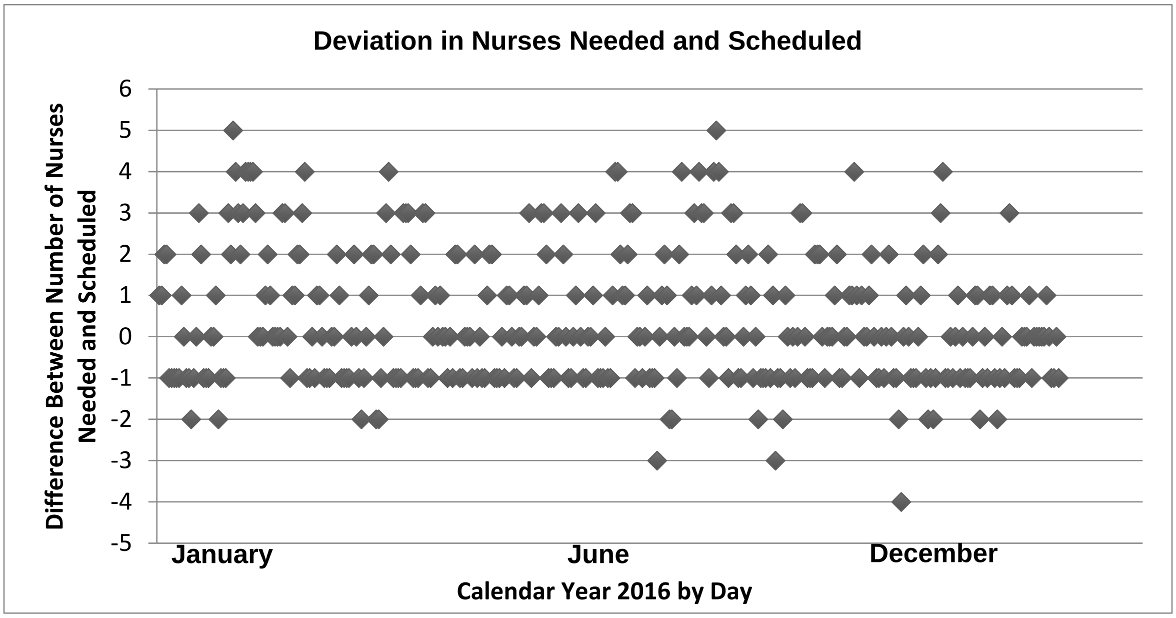

Figure 2.

In addition to underestimating dayshift nurse requirements, the current scheduling methods and practices for this inpatient unit did not account for variation in the number of nurses needed by day of the week. The study's model, however, predicted weekly variation: more nurses needed from Tuesday through Friday, with a gradual tapering off and fewer nurses needed from Saturday through Monday (see Figure 1).

Electronic Scheduling Template Before Model Predictions

Figure 3 is a one-week schedule template that specifies the total number of dayshift nursing needs before model predictions were conducted. The template indicates a need for one 0700-1900 charge nurse (RN CHG- GS 6C) and seven direct care nurses (RN-GS 6C) daily, totaling eight nurses to be scheduled every day. This same template was applied to every week of the year in the electronic scheduling system.

Profile	Coverage Period	Week 1 Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
CNA -GS 6C	0700-1900	2.00	3.00	3.00	3.00	3.00	3.00	3.00
CNA -GS 6C	1900-0700	2.00	3.00	3.00	3.00	3.00	3.00	3.00
RN CHG -GS 6C	0700-1900	1.00	1.00	1.00	1.00	1.00	1.00	1.00
RN CHG -GS 6C	1900-0700	1.00	1.00	1.00	1.00	1.00	1.00	1.00
RN-GS 6C	0700-1900	7.00	7.00	7.00	7.00	7.00	7.00	7.00
RN-GS 6C	1900-0700	7.00	7.00	7.00	7.00	7.00	7.00	7.00

Figure 3.

Electronic Schedule Template Changed—Model Predictions

Figure 4 shows how the staffing template was changed to reflect model predictions for day shift nurses that accounted for variation on the day of the week. Each week of the six-week schedule study period had a different template to reflect the predictions associated with that period. Although Mondays had a lower 0300 census, this Monday shows the same staffing levels as Tuesday. This is due to a correction we made to increase nurse staffing on Mondays because of known surgical patient volume surges experienced mid-morning to early afternoon.

Profile	Coverage Period	Week 2 Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
CNA -GS 6C	0700-1900	2.00	3.00	3.00	3.00	3.00	3.00	3.00
CNA -GS 6C	1900-0700	2.00	3.00	3.00	3.00	3.00	3.00	3.00
RN CHG -GS 6C	0700-1900	1.00	1.00	1.00	1.00	1.00	1.00	1.00
RN CHG -GS 6C	1900-0700	1.00	1.00	1.00	1.00	1.00	1.00	1.00
RN-GS 6C	0700-1900	5.00	7.00	7.00	6.00	6.00	5.00	5.00
RN-GS 6C	1900-0700	7.00	7.00	7.00	7.00	7.00	7.00	7.00

Figure 4.

Discussion

The development of a nurse scheduling forecasting model requires preliminary work to guide the model build and design phase. Those developing the model must first identify what needs to be predicted (the dependent variable). Determining the dependent variable will influence the selection of the independent variables necessary to build the model. This step also requires analyzing the organization's current data repository to assess if the organization has the data collection infrastructure in place for easy extraction of the needed historical data. For this nurse scheduling forecasting model, the desired outcome was to predict the number of nurses needed every day during a defined period of time. To achieve the model prediction, two independent variables were identified: the number of nurses needed each day and the daily patient census at 0300. The unit's past scheduling practices had been derived from hour-per-patient day values calculated from a yearly averaged midnight patient census. This practice was perpetuating the "flaws of average" phenomenon for scheduling, which in turn led to daily over- or understaffing (7) (see Figure 2). The study's model used historical daily patient census data at 0300 to provide more relevant knowledge for accurate schedule predictions for the 0700-day shift, thus reducing over- or understaffing. Patient acuity was also identified as a potential variable for the forecasting model, but the organization did not have a current method to measure and capture the data.

Once the study model was built and validated, the predictions were implemented into an electronic scheduling platform to guide the development of the schedule. The implementation of the model predictions into the electronic scheduling environment provided nursing leadership with a data-driven methodology to support the administrative task of scheduling, which had never been provided before. The study model's support of the nurse schedule allowed the surgical unit's nursing leadership to have greater confidence in schedule design and reduced the administrative time associated with scheduling tasks, such as reworking and reassigning nurses based on loosely predicted needs. The modeling work also provided nursing leadership with new opportunities to talk to employees about current staffing and scheduling challenges and explain how the implementation of the new modeling technique, custom made for their unit, could help improve staffing outcomes. The effort put forth by nursing leadership to engage employees about staffing and scheduling may also have a positive effect on employee engagement and morale associated with nurse staffing (12), though this was not specifically measured or tested for. Future work will be to evaluate the impact of modeling on employee engagement associated with nurse staffing and to determine the effectiveness of the nurse scheduling model by comparing model predictions to actual census and nurses needed during the study period from data sources captured from unit charge nurse and the central staffing office.

Limitations of the study were the inability to account for exogenous variables that were not available for modeling purposes. Examples of exogenous variables that have the potential to impact daily patient census daily counts and overall nurse schedule needs include seasonal trends such as flu outbreaks or surgical case volumes. It also would have been ideal to capture patient daily census numbers closer to the time of 0700 staffing, but organizational patient census data was not available for easy extraction, and therefore the 0300 census was closest point of measure for the model. However, the scheduling needs predicted can be modified to adjust for known patterns, such as mid-morning to early afternoon Monday surgical patient admissions that required additional nurses mid-shift.

Conclusion

Historically healthcare organizations have neglected to devote adequate time and resources to assess the organizational impact of the NSP. Without understanding the scope of the NSP, the possibility of proper solutions that are uniquely designed for each practice environment cannot be developed. The NSP has plagued the profession of nursing for long enough. It is imperative that we shift nursing out of the flaws-of-averages mindset, which has been partially responsible for the misalignment of nursing labor deployment and use (7), and consider more advanced, data-driven scheduling techniques. Therefore, each organization needs to assess its current scheduling practice environment and evaluate potential opportunities to develop a nurse schedule forecasting model. This paper has shown how the development and application of demand modeling with nurse staffing and scheduling data can provide the nursing profession with a feasible solution for addressing the NSP in the current practice environment.

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