Title: IMProving Outcomes Related to Patients Through Advanced Nursing Technology (IMPORTANT)

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Structured Abstract:
Purpose: The purpose of this study was to test the utility of a technology-assisted intervention to increase nurses bedside shift report (BSR) and hourly rounding (HR) and downstream effects on related patient outcomes.

Scope: Patient monitoring by nurses is an essential part of the nurse's role in reducing negative patient outcomes such as patient falls. Patient falls are a major cost to healthcare.
Methods: Remote surveillance devices tracked the nurses' presence at the bedside and alerted the nurse if a patient hadn't been seen for more than an hour. These devices were installed in 32 beds in an acute care setting where they tracked nurses' and patients' activities 24 hours/day, 7 days/week for one year.
Results: On average, nurses managed more than seven patients per shift, spending approximately 9.39 minutes with all patients during a 12-hour shift. This contrasts with earlier studies suggesting higher bedside time, which often relied on incomplete or self-reported data. To optimize nursing workflow and improve patient care, reducing non-nursing tasks and workload is crucial. The study advocates for leveraging remote surveillance to provide nurses with more meaningful interactions at the bedside by minimizing redundant visits. For instance, using such technology during the COVID-19 pandemic could have prevented unnecessary exposures. The findings underscore the potential of technology to enhance patient care and nurse efficiency in monitoring and surveillance.

Key Words: Artificial intelligence, computer vision, nursing, patient falls, patient surveillance

Purpose

The purpose of the study, titled "IMProving Outcomes Related to patients Through Advanced Nursing Technology (IMPORTANT)," was to investigate the impact of a state-of-the-art technology-enabled intervention on enhancing nurse surveillance and its effects on associated nurse-sensitive patient outcomes—falls, pressure ulcer injuries (PUIs), and hospital acquired infections (HAIs)—through the following specific aims:

AIM 1: Utilized data generated by a novel technology ("iN") with the ability to capture bedside interactions, characterized nurse surveillance, including the frequency and duration of bedside shift report (BSR) and hourly rounding (HR), and other nurse interactions at the bedside.

AIM 2: Compared BSR and HR pre-implementation (historical control) and post-implementation to assess the effectiveness of a technology-assisted intervention in increasing BSR and HR.

AIM 3: Controlling for patient characteristics, explored the relationships between technology-enabled BSR, HR, and other nurse interactions at the bedside (collectively termed nurse surveillance) and nurse-sensitive patient outcomes: patient falls, PUIs, and HAIs.

Scope

Background and context. Despite increasing healthcare costs in the United States, critical health outcomes rank lower than other high-resource countries, and many Americans lack high quality care and suffer poor outcomes.[1] In an effort to improve healthcare quality and concomitantly reduce costs, Congress identified serious and expensive but preventable hospital acquired conditions such as patient falls, hospital acquired infections (HAI) and pressure ulcer injuries (PUI) that would no longer be reimbursed by Centers for Medicare and Medicaid Services."[2] There are, for example, nearly 1 million patient falls in hospitals each year which, on average, cost hospitals an additional $17,483 per fall.[3, 4] Increased nursing time with patients has been linked with improved patient and nurse satisfaction as well as reduced risk of adverse events such as patient falls, PUI, HAI, and decreased cost.[5-8] These associations are not surprising given that nurses spend more time with patients than any other healthcare provider. Nurses play a critical role in preventing adverse outcomes by quickly identifying patients at risk, evaluating the extent of these risks, and acting upon the changing status of the patient—a process termed, "nurse surveillance."[8] Hence, nurses are key contributors to overall patient surveillance and safety.[9, 10]

Nurse surveillance has an indispensable function in the detection and prevention of patient deterioration, infection, falls, and pressure ulcer injury.[11] For example, nurses play a critical role in infection prevention both in primary prevention such as education and also secondary prevention as first responders through 24-hour surveillance, allowing them to recognize changes in patient status and patient response to antibiotics.[12] Nurse workload, staffing levels and shift duration have a direct bearing on prevention of HAI;[11] similarly, nurse surveillance is pivotal in preventing falls. Many institutions have attempted to increase nurse surveillance and thereby influence nurse-sensitive outcomes and related healthcare costs.[13-15] Because of the essential role nurse surveillance plays in patient outcomes, BSR and HR are recommended by the Joint Commission and yet, little research has investigated their impact on patient outcomes.[16, 17] Many of the assumptions about the effects of nurse surveillance on patient outcomes have been drawn through indirect measures such as staffing and census levels; all of which have a complex relationship with patient outcomes and none of which fully capture nurse surveillance including BSR and HR.[18-20]

The Joint Commission recommends nurses conduct BSR (i.e. nurses giving report at the bedside with the patient and/or family present) and HR (i.e. having the nurse check on the patient hourly) suggesting they improve patient outcomes by increasing nurse surveillance; nevertheless, there has been little research to assess how or whether BSR and HR are actually carried out, or their contribution to nurse surveillance.[13, 14, 21, 22] To date, the invasive nature of methods such as video surveillance or constant observation has prevented in-depth evaluation of nursing workflow and nurse surveillance.[23] To avoid this, some studies have assessed nurse and patient interactions using work sampling techniques. While time-and-motion studies require continuous observation of the nurse, work sampling is a more efficient statistical method to record observations at intervals and model workflow, and also reduces some of the intrusiveness of the constant observation required with time-in-motion studies.[24-28] However, these studies rely on incomplete data to measure the nursing interactions with patients.

In an effort to increase nursing surveillance via BSR and HR, NewYork-Presbyterian (NYP), a multi-campus hospital, contracted with a company (Inspiren http://inspiren.com), to pilot an innovative technology called “iN,” which is a combination of mounted hardware in the patient room that uses obfuscated computer vision to provide constant surveillance of the patient room, a call bell that operates via Wi-Fi, and companion software supplied via mobile phone app that integrates these technologies. The iN technology (since rebranded as “AUGi”) has color-coded lights that remind the nurse when BSR or HR have not been completed in a timely manner and includes a call bell system that provides alerts directly to nurses, allowing for more rapid responses. While the hospital assessed the influence on nurse and patient satisfaction, this technology generated more comprehensive data on in-room patient mobility, positioning, and interaction with clinicians than other methods, making it possible to generate new knowledge about factors that influence patient outcomes.[24] This novel, technology-enabled intervention intended to improve nurse surveillance through visual cues and mobile alerts had not yet been studied to assess whether the device was associated with increased nurse surveillance or related nursing-sensitive patient outcomes.

Recently, advances in data science suggest that data mining of the Electronic Health Record (EHR) could potentially provide a measure of nurse surveillance, but this approach is limited by the extent to which events such as BSR and HR are properly documented in the EHR.[29] Consequently, there is little evidence regarding the impact of BSR and HR on nurse-sensitive patient outcomes.[30,16, 31, 32] The IMPORTANT study aimed to address the AHRQ’s research priorities to improve healthcare quality by using data resources to “capture important actions and outcomes of healthcare to increase evidence on effective practices,” and “testing and spreading methods and strategies for health care practice improvement to improve health care quality.” This study utilized new technology that allowed for continual observation and recording of patient and nurse activities at the bedside through obfuscated computer vision, capturing activities without compromising patient privacy and rendering a truly comprehensive view of nurse surveillance. Combined with data on patient-sensitive outcomes, a more complete characterization of nurse surveillance and its influence on nursing-sensitive outcomes, as well as the utility of a novel technology to increase BSR and HR, was garnered.

As technology adoption increases, it is important to understand the true benefits; however, technology is frequently adopted without substantial testing on the intended outcomes.[33] With the implementation of this technology, we had an opportunity to provide foundational research that will assist in understanding the actual influence of this and other similar technologies that may emerge on nurse surveillance and nursing-sensitive patient outcomes.

Innovation

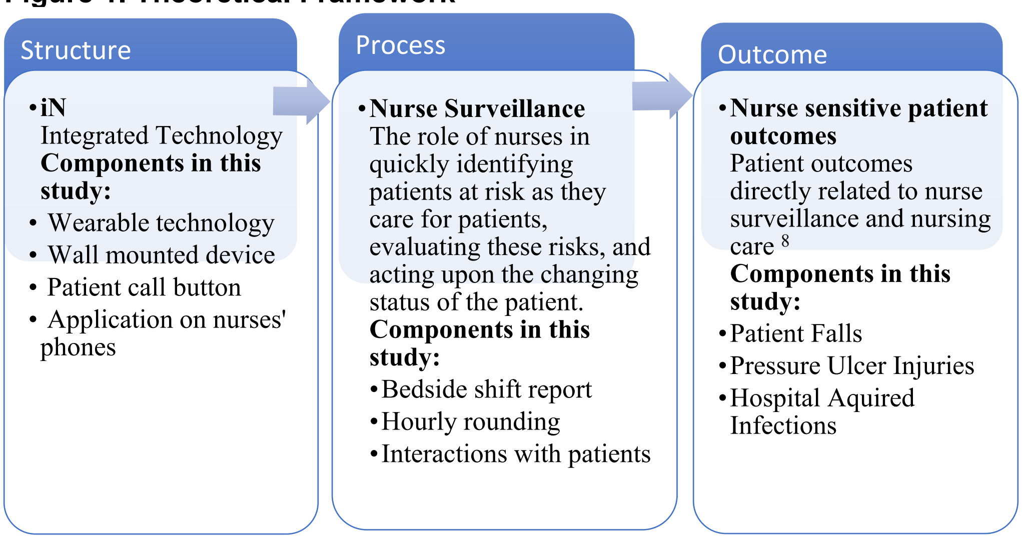
In addition to the fact that this study was the first ever to assess the technology being introduced, to our knowledge, this study was also novel in its capacity to study nurse and patient interactions with continuous observation over a longitudinal period. It was the first time the iN technology had ever been installed in a clinical setting. The wall-mounted device utilized obfuscated computer vision, deep learning, and natural body movement recognition to detect the activity of the nurse in the patient room and assess the presence and position of the patient. The integrated features of the call bell and mobile app were all patented technology that had never been piloted in a clinical setting. This patented technology to support nurse surveillance was novel, and its installation at NYP provided a unique opportunity to address our study aims.

Settings and participants. The study site consisted of two units at NYP Queens, one of the seven campuses of NYP; these units were designated as pilot sites for the iN device by NYP. Each bed on each unit was equipped with iN; both were medical surgical units with approximately 18 beds and three to eight nurses per unit per shift. These units served a diverse population; last year, they averaged 33.4% white, 12.9% Black, ~~1~~9.3% Asian, and 19.9% of patients self-reported as Hispanic, and 14.5% other; 44.7% of these patients were female, and 60% of the patients had multiple chronic conditions.

Methods

Study design. ***Theoretical Framework.*** Utilizing Donabedian's quality of care framework (**Figure 1**), in this study, structure referred to the novel technology supporting and capturing nurse surveillance data. The process component of the model was used to refer to the activities of nurse surveillance as described above. Finally, outcomes referred to the effect these processes had on patients, which in this study were measured by patient falls, PUI, and HAI (**Figure 1**).[34, 35]

Figure 1. Theoretical Framework



Design. This study utilized a prospective cohort study design with nurse surveillance as the exposure and nurse-sensitive patient outcomes as the outcome of interest. Data science techniques were employed to transform data from the iN device into variables, and these data were integrated with other relevant data, as illustrated in the architectural diagram (**Figure 2**), to create a data analytic file addressing the study aims. As depicted in the architectural diagram, data were integrated from various sources (listed in **Table 2**) for each aim. In Aims 1 and 2, predictor variables, confounding variables, and outcome variables were linked using census data to create a single file that was analyzed to form comprehensive surveillance data. In Aim 3, Clinical Data Warehouse (CDW) data added additional information about patient demographics, diagnosis, and co-morbidities (also linked through census data) to determine associations between surveillance and nurse-sensitive outcomes.

Variables and Data Collection Procedures. IRB approvals were obtained, and administrative permission from hospital management at all levels (site, corporate, senior level management) was secured.

Currently, the optimal time recommended for BSR is less than five minutes,[36] and yet the length of this interaction can vary widely depending on the nature of the patient and nurse relationship.[37] For example, for a patient nearing discharge who is relatively stable and has been cared for by both nurses giving the report, the interaction may be very brief, consisting of reintroducing the nurse assuming care, reporting that there are no changes in condition, no planned procedures, and asking whether the patient has any questions. Therefore, the minimum time selected by NYP for BSR was set at 1 minute within an hour of change of shift. Therefore, this is the length of time used for the BSR variable in this study. **Table 2** details the main study variables, data sources, and collection methods.

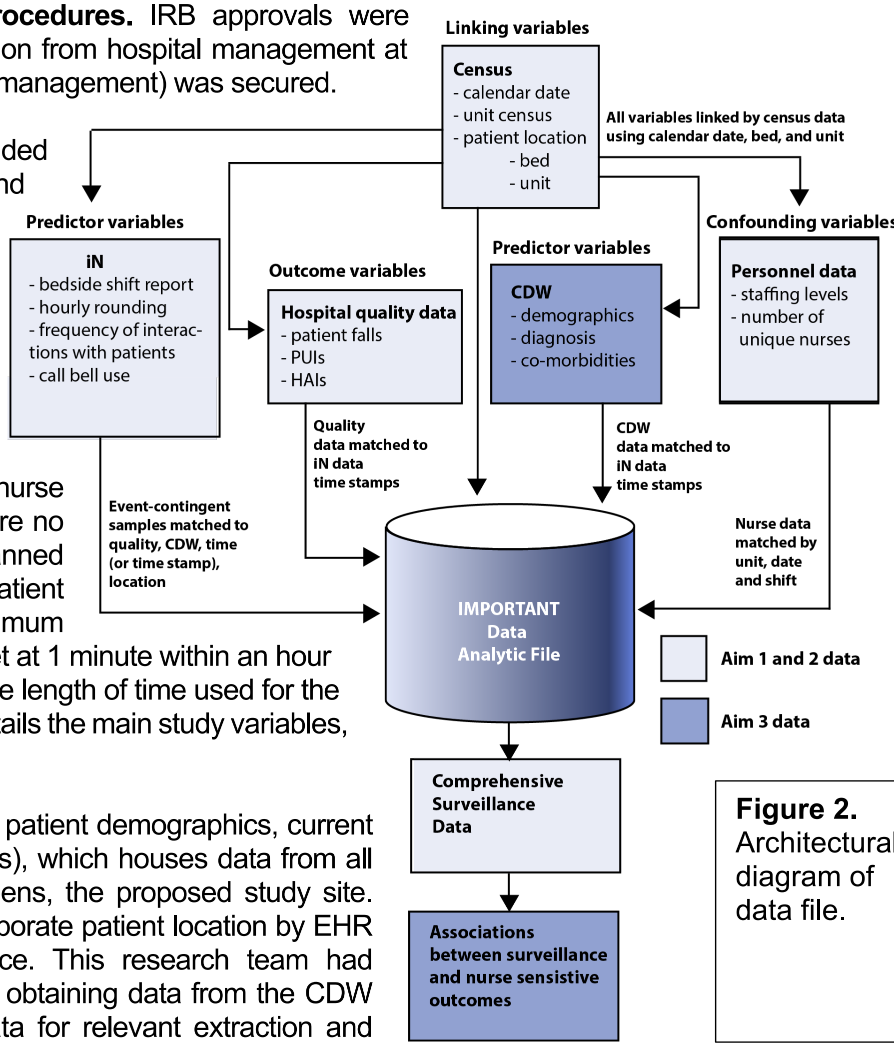


Figure 2. Architectural diagram of data file.

EHR data came from the CDW (e.g., patient demographics, current primary diagnoses, and co-morbidities), which houses data from all NYP campuses, including NYP Queens, the proposed study site. Census data were also used to corroborate patient location by EHR and data collected on the iN device. This research team had extensive experience requesting and obtaining data from the CDW and formatting and storing CDW data for relevant extraction and analysis.

The CDW at CUIMC of NYP provided an enterprise master patient index containing over 5.5 million patient records. Information stored in the CDW was accessed and is being used to complete Aim 3 of the proposed project. The CDW contained inpatient, outpatient, and ancillary data from the clinical data repository and electronic health records. Data types included demographics, visit histories, diagnoses, lab results, medication orders and dispensing information, problems, allergies, etc. It was the most comprehensive data source at the medical center, containing all the data sources needed for Meaningful Use attestation. Data for NYP were requested through the CUIMC Tripartite Request Assessment Committee (TRAC), the data governance mechanism for requesting data, including CDW, census, and quality data for all NYP campuses, including NYP Queens, the study site. As described in the institutional resources, Dr. Cato was the Columbia University School of Nursing liaison for TRAC requests, and he assisted in facilitating requests and gathering data. **Figure 2** displays the architectural diagram of the creation of the IMPORTANT data analytic file.

Data were collected by patient beds (each bed had an iN device) which recorded all activity of the nurse and patient in the room, such as whether or not the patient was present, patient movement, and movements of the nurse(s). Guided by our pilot studies where nurses were with patients in 0.06 of the total observations, we could expect to minimally observe 75,768 interactions with patients in a year-long period: (.06 observations of nurses with patients) X (15-minute intervals) X (average census of 18 patients/unit) X (2 units) X (4 intervals/hour) X (24 hours/day) X (365 days/year).

Table 2: Main Study Variables at Patient Level Over 12 months

Variable	Functional Definition	Variable Type
Source: iN device, Data collected and delivered via the cloud		
Bedside shift report by nurses	Two nurses at bedside for >1 minute at least once per 12 hour shift within 1 hour of change of shift.	Continuous (number per 12 hour shift)
Hourly Rounding by nurses	Nurse at bedside for >5 seconds at least once per hour	Continuous (number per 12 hour shift)
Frequency of nurse interactions with patients	Number of times nurse is at bedside during 12 hour shift	Continuous (number per 12 hour shift)
Total time spent with patient per shift	Total time spent with patient during 12 hour shift	Continuous (number per 12 hour shift)
Other interactions	More than one visit per hour lasting any length of time (could be categorized by number of providers present, length of time, etc.)	Continuous (number per 12 hour shift)
Patient frequency of call bell use	Number of calls by patient to nurse per 12 hour shift	Continuous (number of calls to nurse per shift) per 12 hour shift
Source: Existing hospital quality data collected through NYP Quality Department, reported according to national reporting standards		
Patient falls	Existing assisted and unassisted falls data as defined by National Database of Nursing Quality Indicators (NDNQI)	Categorical (Yes or No) per 12 hour shift
HAI outcomes	Existing Central Line-Associated Blood Stream Infections, Catheter-Associated Urinary Tract Infections and Methicillin-resistant Staphylococcus aureus (MRSA) bacteremia rate data as defined by National Healthcare Safety Network, aggregated to include all types of HAI	Categorical HAI (Yes or No) per 12 hour shift
PUIs	Existing PUI data, reported by hospital Quality department to NDNQI	Categorical PUI (Yes or No) per 12 hour shift
Census data	Number of patients on the unit during the shift	Continuous (number per 12 hour shift)
Patient location	Patient location by bed and unit	Categorical
Source: Existing hospital data collected through NYP Personnel Department		
Nurse staffing data	Number of unique nurses during the shift Staffing ratios? on the unit per shift	Continuous (number per 12 hour shift)
Source: Electronic health record data requested through Clinical Data Warehouse		
Patient demographics	Age Sex Race/Ethnicity (as defined by the United States Census)[38, 39]	Age: Continuous Sex: Categorical (Male, Female, Other) Race (White, Black/African American, American Indian or Alaska Native, Asian, Native Hawaiian or Other Pacific Islander) Ethnicity: Categorical (Hispanic or Latino Yes, or No)
Current Diagnoses	Reason for current hospitalization	Categorical (number of categories will be dependent on findings)
Co-morbidities	Other diagnoses	Categorical (other diagnoses, dependent on findings)

Note: Aim 1 and 2 data; Aim 3 data

We have many more recorded observations because *every* interaction was recorded (rather than observations that occurred as discrete events in 15-minute intervals). These data were time and location stamped which was used to map each observation with data on PUIs, HAIs, and falls, as well as patient-specific data from the EHR, including patient demographics (age, gender, race/ethnicity), comorbidities (identified using ICD-10 codes), and the reason for current hospitalization (also identified by ICD-10 codes). Comorbidities were categorized according to the adjusted risk of mortality using the Charlson Comorbidity Index.[40-42] The hospital quality department collected data on falls, PUIs, and HAIs, which could be obtained as either discrete event data or incidence rate; the discrete event data were used to match the level of the nurse interaction data and verify this with patient-level data from the EHR. Call bell use logs were also integrated into the IMPORTANT data analytic file from the iN technology data. Call bell logs provided an additional factor that may contribute to the effects on patient outcomes and could be correlated with the nurse interactions at the bedside to assess the relationship between response time of the nurse and patient falls.

Currency of the data (whether events in the EHR were timely enough to provide meaningful data) as well as concordance (agreement with other data), important considerations in assessing data quality, were assessed by checking the time of events as recorded by the iN device with the time of events as recorded in the EHR.[29] Census data were used to link patient EHR number to a specific calendar date, bed, and unit location.[29]

Data analyses

In **Aim 1,** surveillance characterization, including the frequency and duration of BSR and HR, along with other nurse interactions at the bedside, was conducted using data collected by the iN device. According to NYP security protocol, the data collected by the iN device was stored in the Amazon cloud; this data was stored as comma-separated values (CSV) and was imported directly into SAS. Once imported into the data analysis software, this data was aggregated to represent event-contingent data (rather than continuous or repeated data) variables, enabling the extraction of data such as BSR by nurses, HR by nurses, frequency of nurse interactions with patients, and other interactions at each bed from the iN device.

Predictor variables were created per bed shift (day shift: 07:30-19:29 per calendar date; night shift: 19:30-07:29 per calendar date) by aggregating data for each predictor collected from the iN device at each bed on each shift. From this bed shift-level data, descriptive statistics on nurse interactions at the bedside, such as frequency, duration, and total time spent with nurses, were generated. Previous literature has emphasized that all activities of the nurse that allow for observation of the patient have a cumulative effect over time; therefore, all interactions with the patient, regardless of the primary intent, were incorporated. Data analyses were conducted by Dr. Sun and Caroline Fu. A manuscript is currently under review.

In **Aim 2,** we compared the BSR and HR pre-implementation (historical control) and post-implementation data to assess the utility of a technology-assisted intervention in increasing BSR and HR.

Unfortunately, the data generated by Aim 1 were too different to be meaningfully compared for statistical significance with data from the preliminary study to test whether the iN device was associated with a change in BSR and HR, so we reported the change in percentage.

For **Aim 3**, **controlling for patient characteristics, explore the relationship between technology-enabled nurse surveillance and nurse-sensitive patient outcomes: patient falls, PUIs, and HAIs**, data will be analyzed at patient daily level. Because of extensive delays related to the COVID-19 pandemic (all research was stopped by the institutions) and subsequent delays with IRB approval, data extraction, and personnel changes, we are still working to complete Aim 3. Aim analyses are being conducted by Dr. El Samuels, a biostatistician with Hunter-Bellevue School of Nursing; analyses should be completed by May 2024.

Dichotomized patient outcomes such as patient falls, HAIs and PUIs at patient daily level will be collected from hospital quality data. This patient outcome data will be linked to patient covariates such as demographic information, current diagnosis, and comorbidities through the admission account number, which is a unique ID for each admission. Next, the patient daily outcomes with patient level covariates will be matched to census data through account number and calendar date of hospital stay to identify the patient location by room and bed on each hospital day. Then patient daily outcomes and predictor variables aggregated through data collected from in device per bed shift will be linked by bed and calendar date. From the patient daily level data we will assess the correlation between nurse interactions and patient outcomes. The outcome of interest for this aim is days from admission to HAIs, PUI, and patient falls. This is a time-to-event outcome, and we will use cox-proportional hazards regression model to assess **Aim 3**. The predictor variables include (1) patient level variables (noted as $\boldsymbol{X}0\boldsymbol{ij}$k) which include demographics (age, race, etc.) and acuity/severity of illness at admission (comorbidities, diagnoses, and acuity level are captured within the hospital EMR and staffing data.); (2) time-dependent daily patient-level factors such as patient movement or procedures performed during hospital stay (noted as **X1**$\boldsymbol{ij}$k($\boldsymbol{t}$)); (3) time-dependent daily bed-level variables such as BSR and HR, nurse surveillance (e.g., total time spent with patient) (noted as **Y**jk($\boldsymbol{t}$)); and (4) daily unit-level factors such as nurse staffing (noted as **Z**k($\boldsymbol{t}$)); We will use a Cox-proportional hazard model with time-dependent covariates. For patient i on bed j from unit k, the hazard of HAI at day t, hijk(t), is modeled as:

$$hij\text{k}(t)=\lambda o(t)exp(\beta 1\boldsymbol{X}0\boldsymbol{ij}\text{k(t)} +\beta 2\boldsymbol{X}1\boldsymbol{ij}\text{k(t)} +\beta 3\boldsymbol{Yj}\text{k}(\boldsymbol{t})+\beta 4\mathbf{Z}\text{k}(\boldsymbol{t})+\mu ij\text{k},$$

where $\lambda o(t)$ is baseline hazard function and μijk is patient level random effect for a random-effect Cox model. To account for the temporal relationship between nurse interactions and HAIs and the infection incubation period, daily nurse interaction information two days before the onset of an HAI will be used as time-dependent covariates.[43, 44] Prior to building the final multivariable regression model, bivariate relationships between each predictor and outcome will be assessed. Predictors with a *p*-value <0.10 from bivariate analysis will be entered into the cox-proportional hazards regression model. Key assumptions of the model will be assessed. The outcome is a dichotomized outcome from time to admission, but the predictors can be either dichotomized or continuous. Adjusted hazard ratios, ratios of risk per unit time, and 95% confidence intervals will be reported to assess the size and direction of the effects of nurse intervention on nurse-sensitive patient outcomes. If the predictor is dichotomous then the amount of nurse-sensitive patient outcome (HAI, PUI, or patient fall) risk per unit time decreased or increased in intervention group (or the group with greater nurse interaction) as compared to control group, will be reported from survival model (cox regression model). If the predictor is treated as continuous, then the amount of outcome risk per unit time decreased or increased for one-unit increase in the predictor will be reported from survival model. Therefore, this model works for predictors as either dichotomized or continuous. For outcomes such as PUI that might have different stages, we will also explore regression models where the outcome is an ordinal scale such as proportional-odds cumulative logit model. All analyses will be performed in SAS Version 9.4 (SAS Institute, Inc., Cary, NC).

Data Management. All data were stored in a password-protected file created, maintained, and analyzed by the behind the CUIMC firewall. An architectural diagram of data and main study variables are included in Figure 2 and Table 2 (respectively). These measures have been validated and used extensively by research team members.

Limitations. The underreporting of HAIs, PUIs, and falls may reduce the accuracy of our data.[45, 46] We are able to mitigate some of this by correlating data from the iN device with these outcomes. We can use this data to validate the falls reported by the hospital which will help ensure correctness (whether the Quality/National Database of Nursing Quality Indicators data is true) of the data gathered.[29] In regards to the iN device, it is possible that through the implementation of the iN device, nurses became aware of the iN device and worked more carefully to reduce HAI, PUI, or falls. However, this would be a positive outcome. Moreover, over time, nurses are likely to return to normal habits.

Using EHR as secondary data also poses challenges in terms of quality of data.[29] Correctness and concordance (agreement between EHR and other data) will be addressed through validating EHR data against other data. For example, although algorithms can be used to identify HAI in the EHR data, incidents of specific HAIs are reported to the NYP quality department for reporting to NDNQI. By running reported HAIs against those found in the EHR, we can assess for correctness and concordance. Plausibility (i.e., does the data make sense based on current evidence?) of PUI, HAI, and falls data will be assessed by comparing data with historic levels of each for the specific units where the research is being conducted.[29] Collecting primary and secondary data and managing large datasets has inherent challenges. In conjunction with the excellent support of an experienced research team, the PI's prior experience managing existing datasets will support effective anticipation and management of these challenges. Reliance on secondary data from hospital departments may also be a limitation, though using established metrics and definitions that are known to departments has helped mitigate this problem.

Results

For a period of 12 months, iN captured all activity at the patient bedside. The two units, with a combined average daily patient census of 16.84, accommodated 17.5 nurses with an average of 5.36 years of service. Among the nursing staff, 92% held a Bachelor of Science in Nursing (BSN), and the certification rate was 20%. A total of n=408,588 interactions from 37 beds and 49 nurse users over 670 shifts were analyzed (Table 2). Nurses' interactions with patients were observed 1.53 times more often during day shifts (n=247,273) compared to night shifts (n=161,315). The mean interaction time with a patient was 3.34 seconds longer during nights than days ($p>0.01$). A Mann-Whitney U-Test comparing mean interaction time between day shift (1) and night shift (2) revealed that day shift mean interaction time was 3.34 seconds shorter than the night shift, which was statistically significant (sd 0.32, $p<0.001$). However, nurses spent more time in total with patients on the day shift.

For each nurse, the mean number of interactions per bed was 7.86 (standard deviation [sd] 10.13); the mean total time of interactions per bed was 9.39 minutes (sd 14.16). On average, nurses visited patients in 7.43 beds (sd 4.03) (Day shift: Mean 7.80 beds per nurse per shift, sd 3.87; Night shift: Mean 7.07 per nurse per shift, sd 4.17).

BSR was completed 20.72% of the time on average: on the day shift 19.74% of the time (n=2289) versus 21.69% on the night shift ($X = 0.0037$, $p < 0.05$). HR was completed 52.68% on average. HR was done 60.25% of the time on the day shift (n=83,842) and 45.11% (n=58,551) on the night shift, which was statistically significant ($X < 0.00001$, $p < .05$). The mean time per HR was 69.5 seconds (sd=98.07) and 50.1 seconds (sd=56.58) for BSR. Our previous data indicated BSR was only conducted on this site 3% of the instances in which there was an opportunity to do so; this represented a 17.72% increase. Previously, HR had been conducted in 35.1% of the instances where there was an opportunity to do so prior to the implementation of the devices. This represented a 17.58% increase in HR.

The 37 beds were occupied on average for 90.4% (range from 76% to 97%) of shifts during the study period. The mean time per HR was 69.5 seconds (sd=98.07) (Table 2) and 50.1 seconds (sd=56.58) for BSR.

While our analysis indicated that nurses visited patients more often during the day shift, the average interaction time with patients was longer during the night shift. During a 12-hour shift, on average, nurses visited the patient bed 7.86 times. However, on average, the total time spent at the bedside was 10.62 minutes during the day and 8.02 during the night shift. Our study suggests that, regardless of the number of patients assigned, nurses visit more patients, on average, during day shifts than night shifts, amounting to more time on average at the bedside but stretched over a greater number of patients, resulting in statistically significantly shorter visits than on the nightshift. Without this objective data, it is hard to make a case for the benefit of nursing time at the bedside or for increasing nurse-to-patient staffing ratios. In this study, nurses cared for nearly 8 patients on the day shift and 7 on the night shift: regardless of their shift assignment. This suggests that a strict ratio may not be the only change needed to ensure nurses have adequate time with patients.

Bedside shift report was more frequently conducted on the night shift. This could indicate that as the morning shift arrives, there is a more structured process for providing handoff, but this could be explored further in future studies. Hourly rounding was more often conducted during the day shift, which is consistent with the idea that patients would be asleep at night. This provides some verification of the validity of the data, as one might argue that checking on a patient hourly during sleeping hours could be disruptive to the patient's well-being.

Overall, nurses had more than seven patients per shift, and the total time spent with all patients per shift was 9.39 minutes on average throughout 12 hours. Previous studies have suggested a far higher amount of time that nurses spent at the bedside—some as much as 37% of their shift.[47] However, as aforementioned, these studies rely on incomplete or self-reported data. Improving nursing workflow and reducing nursing workload, as well as the number of non-nursing tasks, could improve the amount and quality of time nurses spend with patients. With nurses spending only 9.39 minutes at the bedside per patient per 12-hour shift, the use of remote surveillance of patients may allow nurses to have more time for meaningful interactions at the bedside and fewer redundant visits. For example, if a nurse is completing hourly rounding but the patient has just been seen by another nurse or other staff member, the practice may not only not be helpful but may introduce unnecessary exposures to infectious agents (such as during the COVID-19 pandemic).

The surveillance of nurses may have both positive and negative implications. For example, surveilling nurses may provide increased security, risk management, and enhanced productivity for employers. However, nurses may perceive surveillance as diminishing privacy, cause anxiety or distrust of their employer, or fear an abuse of power by employers.[48] However, because of the way this data was collected, much can be learned about how to improve the workflow of nurses to reduce workload burden or decrease redundancy of care while maintaining the privacy of both the nurses and patients. The ability to quantify nursing interactions could be used in future studies to detect how nursing interactions affect patient outcomes, such as hospital-acquired infections, pressure ulcer injuries, and patient falls. There are many factors that influence the amount of time nurses are at the bedside, including staffing, patient acuity, etc. The purpose of this study was not to account for all possible factors but to establish a baseline for how much time, on average, nurses spend at the bedside in direct patient care, regardless of these or other extemporaneous factors. By collecting data 24 hours/day, for an entire year, over multiple units, and several beds, we were able to state the average time at the bedside, in this setting.

Existing studies have relied on self-reported data to determine how and whether nursing interactions (such as bedside shift report and hourly rounding) influence patient outcomes. Data collected from this study were integrated with electronic health record data to determine how nurse-sensitive outcomes are affected by the interaction of the nurse at the bedside in future studies, which could help determine the optimal ratio of nurse-to-patient interactions.

List of Publications and Products

1. **Sun, C.,** Fu, C., Levin, A., Cato, K. (2022). How much time do nurses really spend at the bedside? AMIA 2022 Informatics Summit. Poster presentation. Chicago, IL.

2. **Sun, C.,** Fu, C., Cato, K. (2024). Characterizing Nursing Time With Patients Using Computer Vision. *Journal of Nursing Scholarship. Under Review.*

REFERENCES

1. McGlynn EA, Asch SM, Adams J, et al. The quality of health care delivered to adults in the United States. *New England journal of medicine* 2003; 348: 2635-2645.
2. Centers for Medicare and Medicaid Services. *CMS-1533-FC. Medicare Program; Changes to the Hospital Prospective Payment System and Fiscal Year 2008 Rates.* . 2007.
3. Trepanier S. A hospital system approach at decreasing falls with injuries and cost. *Nursing economic$* 2014; 32: 135.
4. Agency for Healthcare Research and Quality. Preventing Falls in Hospitals. A toolkit for improving quality of care., https://www.ahrq.gov/professionals/systems/hospital/fallpxtoolkit/index.html (2017, accessed April 20 2017).
5. Aiken LH, Clarke SP, Sloane DM, et al. Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction. *Journal of the American Medical Association* 2002; 288: 1987-1993.
6. Duffield C, Diers D, O'Brien-Pallas L, et al. Nursing staffing, nursing workload, the work environment and patient outcomes. *Applied Nursing Research* 2011; 24: 244-255.
7. Crisp N and Chen L. Global supply of health professionals. *New England Journal of Medicine* 2014; 370: 950-957. 2014/03/07. DOI: 10.1056/NEJMra1111610.
8. Kutney-Lee A, Lake ET and Aiken LH. Development of the hospital nurse surveillance capacity profile. *Research in nursing & health* 2009; 32: 217-228.
9. Dresser S. The role of nursing surveillance in keeping patients safe. *Journal of Nursing Administration* 2012; 42: 361-368.
10. Institute of Medicine (US) Committee on the Work Environment for Nurses and Patient Safety. *Keeping Patients Safe: Transforming the Work Environment of Nurses.* 2004. Washington (DC): National Academies of Sciences Engineering Medicine.
11. Zingg W, Holmes A, Dettenkofer M, et al. Hospital organisation, management, and structure for prevention of health-care-associated infection: a systematic review and expert consensus. *The Lancet Infectious Diseases* 2015; 15: 212-224.
12. Olans RN, Olans RD and DeMaria Jr A. The critical role of the staff nurse in antimicrobial stewardship—unrecognized, but already there. *Clinical Infectious Diseases* 2015; 62: 84-89.
13. Toussaint JS and Berry LL. The Promise of Lean in Health Care. *Mayo Clinic Proceedings*; 88: 74-82. DOI: 10.1016/j.mayocp.2012.07.025.
14. Rutherford P, Bartley, A, Miller D, et al. *Transforming Care at the Bedside How-to Guide: Increasing Nurses' Time in Direct Patient Care*. 2008. Cambridge, MA: Institute for Healthcare Improvement.
15. Wilson G. Implementation of releasing time to care–the productive ward. *Journal of nursing management* 2009; 17: 647-654.
16. Mardis T, Mardis M, Davis J, et al. Bedside shift-to-shift handoffs: a systematic review of the literature. *Journal of nursing care quality* 2016; 31: 54-60.
17. Taylor E and Hignett S. The scope of hospital falls: A systematic mixed studies review. *HERD: Health Environments Research & Design Journal* 2016; 9: 86-109.
18. Subirana M, Long A, Greenhalgh J, et al. A realist logic model of the links between nurse staffing and the outcomes of nursing. *Journal of Research in Nursing* 2014; 19: 8-23.
19. Aiken LH, Sloane DM, Bruyneel L, et al. Nurse staffing and education and hospital mortality in nine European countries: a retrospective observational study. *The Lancet* 2014; 383: 1824-1830.
20. Cho E, Sloane DM, Kim E-Y, et al. Effects of nurse staffing, work environments, and education on patient mortality: an observational study. *International journal of nursing studies* 2015; 52: 535-542.

21. The Joint Commission. Center for Transforming Healthcare aims to prevent inpatient falls with injury, https://www.jointcommission.org/assets/1/23/jconline_april_30_141.pdf (2014, accessed October 1 2018).
22. The Joint Commission. Guide to Patient and Family Engagement in Hospital Quality and Safety, https://www.jointcommission.org/guide_to_patient_and_family_engagement_in_hospital_safety_and_quality_/ (2013, accessed October 1 2018).
23. Bharucha AJ, London AJ, Barnard D, et al. Ethical considerations in the conduct of electronic surveillance research. *The Journal of Law, Medicine & Ethics* 2006; 34: 611-619.
24. Pelletier D and Duffield C. Work sampling: valuable methodology to define nursing practice patterns. *Nursing & health sciences* 2003; 5: 31-38.
25. Kirkland KB and Weinstein JM. Adverse effects of contact isolation. *The Lancet* 1999; 354: 1177-1178.
26. Cohen B, Hyman S, Rosenberg L, et al. Frequency of Patient Contact with Health Care Personnel and Visitors: Implications for Infection Prevention. *Joint Commission journal on quality and patient safety / Joint Commission Resources* 2012; 38: 560-565.
27. Keely EJ and Forster AJ. Time-motion studies of internal medicine residents' duty hours: a systematic review and meta-analysis. *Advances in Medical Education and Practice* 2015; 6: 621.
28. Blay N, Duffield, C.M., Gallagher, R., Roche, M. Methodological integrative review of the work sampling technique used in nursing workload research. *Journal of advanced nursing* 2014; 70: 2434-2449. DOI: 10.1111/jan.12466.
29. Weiskopf NG and Weng C. Methods and dimensions of electronic health record data quality assessment: enabling reuse for clinical research. *Journal of the American Medical Informatics Association* 2013; 20: 144-151.
30. Wejr P. Non-nursing duties. *Young* 2010; 539: 548.
31. Finkler SA, Knickman JR, Hendrickson G, et al. A comparison of work-sampling and time-and-motion techniques for studies in health services research. *Health services research* 1993; 28: 577.
32. Rondinelli JJ. Hourly rounding implementation: a multisite description of structures, processes, and outcomes. *The Journal of nursing administration* 2012; 42: 326-332. DOI: 10.1097/NNA.0b013e31824ccd43.
33. Colicchio TK, Facelli JC, Del Fiol G, et al. Health information technology adoption: Understanding research protocols and outcome measurements for IT interventions in health care. *Journal of Biomedical Informatics* 2016; 63: 33-44. DOI: https://doi.org/10.1016/j.jbi.2016.07.018.
34. Agency for Healthcare Research and Quality. Preventing Falls in Hospitals: 5. How do you measure fall rates and fall prevention practices?, (2013, 2017).
35. Montalvo I. The National Database of Nursing Quality Indicators. *Online Journal of Issues in Nursing* 2007; 12.
36. Agency for Healthcare Quality (AHRQ). Nurse BSR Implementation Handbook, https://www.ahrq.gov/sites/default/files/wysiwyg/professionals/systems/hospital/engagingfamilies/strategy3/Strat3_Implement_Hndbook_508.pdf (accessed 8/11 2021).
37. Athwal P, Fields W and Wagnell E. Standardization of change-of-shift report. *J Nurs Care Qual* 2009; 24: 143-147. 2009/03/17. DOI: 10.1097/01.ncq.0000347451.28794.38.
38. Census US. United States Census: Race, https://www.census.gov/topics/population/race/about.html (2018).
39. www.census.gov Race and Ethnicity, https://www.census.gov/mso/www/training/pdf/race-ethnicity-onepager.pdf (accessed 2018 June 27).

40. Charlson M, Szatrowski TP, Peterson J, et al. Validation of a combined comorbidity index. *Journal of clinical epidemiology* 1994; 47: 1245-1251.
41. Deyo RA, Cherkin DC and Ciol MA. Adapting a clinical comorbidity index for use with ICD-9-CM administrative databases. *Journal of clinical epidemiology* 1992; 45: 613-619.
42. Sundararajan V, Henderson T, Perry C, et al. New ICD-10 version of the Charlson comorbidity index predicted in-hospital mortality. *Journal of clinical epidemiology* 2004; 57: 1288-1294.
43. Shang J, Needleman J, Liu J, et al. Nurse Staffing and Healthcare Associated Infection, Unit-level Analysis. Journal of Nursing Administration, Under review, 2018.
44. Weinstein RA, Stone PW, Pogorzelska M, et al. Hospital staffing and health care–associated infections: a systematic review of the literature. *Clinical Infectious Diseases* 2008; 47: 937-944.
45. Lee AS, Cooper BS, Malhotra-Kumar S, et al. Comparison of strategies to reduce meticillin-resistant Staphylococcus aureus rates in surgical patients: a controlled multicentre intervention trial. *BMJ open* 2013; 3: e003126.
46. Hale WA, Delaney MJ and Cable T. Accuracy of patient recall and chart documentation of falls. *The Journal of the American Board of Family Practice* 1993; 6: 239-242.
47. Westbrook JI, Duffield C, Li L, et al. How much time do nurses have for patients? A longitudinal study quantifying hospital nurses' patterns of task time distribution and interactions with health professionals. *BMC Health Serv Res* 2011; 11: 319. 2011/11/25. DOI: 10.1186/1472-6963-11-319.
48. Wallace R. Electronic surveillance of nurses in the workplace: Ethical considerations. *OJIN: The Online Journal of Issues in Nursing* 2018; 23.