Received: 4 October 2023 | Revised: 20 March 2024 | Accepted: 3 April 2024

DOI: 10.1111/jnu.12971

JOURNAL OF NURSING SCHOLARSHIP

Characterizing nursing time with patients using computer vision

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Funding information
Agency for Healthcare Research and Quality, Grant/Award Number: R03 HS27006-01A1

Abstract

Background: Compared to other providers, nurses spend more time with patients, but the exact quantity and nature of those interactions remain largely unknown. The purpose of this study was to characterize the interactions of nurses at the bedside using continuous surveillance over a year long period.

Methods: Nurses' time and activity at the bedside were characterized using a device that integrates the use of obfuscated computer vision in combination with a Bluetooth beacon on the nurses' identification badge to track nurses' activities at the bedside. The surveillance device (AUGi) was installed over 37 patient beds in two medical/surgical units in a major urban hospital. Forty-nine nurse users were tracked using the beacon. Data were collected 4/15/19–3/15/20. Statistics were performed to describe nurses' time and activity at the bedside.

Results: A total of $n=408{,}588$ interactions were analyzed over 670 shifts, with >1.5 times more interactions during day shifts ($n=247{,}273$) compared to night shifts ($n=161{,}315$); the mean interaction time was 3.34 s longer during nights than days ($p<0.0001$). Each nurse had an average of 7.86 (standard deviation [SD] = 10.13) interactions per bed each shift and a mean total interaction time per bed of 9.39 min (SD = 14.16). On average, nurses covered 7.43 beds (SD = 4.03) per shift (day: mean = 7.80 beds/nurse/shift, SD = 3.87; night: mean = 7.07/nurse/shift, SD = 4.17). The mean time per hourly rounding (HR) was 69.5 s (SD = 98.07) and 50.1 s (SD = 56.58) for bedside shift report.

Discussion: As far as we are aware, this is the first study to provide continuous surveillance of nurse activities at the bedside over a year long period, 24 h/day, 7 days/week. We detected that nurses spend less than 1 min giving report at the bedside, and this is only completed 20.7% of the time. Additionally, hourly rounding was completed only 52.9% of the time and nurses spent only 9 min total with each patient per shift. Further study is needed to detect whether there is an optimal timing or duration of interactions to improve patient outcomes.

Clinical Relevance: Nursing time with the patient has been shown to improve patient outcomes but precise information about how much time nurses spend with patients has been heretofore unknown. By understanding minute-by-minute activities at the bedside over a full year, we provide a full picture of nursing activity; this can be used in the future to determine how these activities affect patient outcomes.

KEYWORDS
biometry, computer vision, computers, decision support, hospital, medical-surgical nursing, nursing staff, patients, technology

BACKGROUND

Although research has indicated that raising the ratio of nurses to patients might lower mortality rates, medication errors, instances of pneumonia, the utilization of patient restraints, and various other nurse-related outcomes, accurately quantifying the advantages is challenging without understanding the impact of nurse-to-patient ratios on the duration of time nurses can allocate to individual patients (Driscoll et al., 2018).

Nurses are the largest component of the healthcare workforce (U.S. Bureau of Labor Statistics, 2019) and spend more time with patients than any other profession (Butler et al., 2018). Nurses frequently notice the first signs of patient deterioration and are considered the last line of patient defense (Joy, 2009); both rely on the nurses' presence at the bedside. However, the exact amount of time a nurse spends at the bedside remains largely unknown. Some of the reasons nurses are at the patient's bedside are related to policy requirements that are designed to improve patient safety and related outcomes. For example, bedside shift report (BSR) is recommended by the Joint Commission (Joint Commission, 2017). When performing BSR nurses give report (i.e., hand over the patient to the next nurse) at the patient's bedside, with the intent of reducing errors and improving the continuity of care; hourly rounds (HR) are also recommended to improve patient outcomes (Agency for Healthcare Quality (AHRQ)). However, the relationship of BSR and HR to patient outcomes remains understudied. To explore the activities of nurses at the bedside, this study expands on a previous pilot study conducted by our research team (over a 6-month period) to encompass a full calendar year (Sun et al., 2021).

Historic studies have suggested that nurses spend up to 37% of their shift in direct patient care (Westbrook et al., 2011). However, these existing studies on nursing activities at the bedside rely mainly on self-report or methods such as "time-in-motion," "Work Observation Method by Activity Timing (WOMBAT)," or "work sampling," which are approximations but do not obtain a detailed record over an extended period (Leafloor et al., 2015, 2017; Westbrook et al., 2011). While video surveillance may be a viable alternative, there are few of these types of studies due to privacy issues (van Dalen et al., 2019). Some suggest that data science could employ machine learning or other data science techniques to use electronic health record (EHR) data to calculate nurse surveillance. However, the effectiveness of this approach is hindered by the accuracy and completeness of documenting events like BSR and HR within the EHR (Weiskopf & Weng, 2013). With the advent of artificial intelligence (AI) and computer vision, there is an opportunity to more precisely quantify nurse activity at the bedside which could be coupled with data on patient outcomes to provide a deeper understanding of how nursing activities affect patient outcomes.

Nurses have developed a novel technology called "AUGi" (available at inspiren.com) that shows promise in addressing some of the challenges associated with recent technological solutions aimed at healthcare workload reduction and fall prevention. These solutions typically fall into three categories: wearable devices, vision-based systems, and ambient devices (Mubashir et al., 2013). For instance, "Falldroid" offers early fall detection and alerts staff promptly, but its reliance on patients wearing sensors poses issues, particularly for forgetful patients or those preferring non-wearable options (Demiris et al., 2008; Shahzad & Kim, 2018; Stone & Skubic, 2014; Walsh et al., 2018). Ambient methods, which integrate audio and video, face challenges in accurately distinguishing noise, impacting their accuracy (Li et al., 2012, 2013; Mubashir et al., 2013). Liu and Ostadabbas utilized computer algorithms and webcams (vision methods) to detect patient falls based on positioning, but is constrained by the need for a clear view of the patient (i.e., cannot be under covers or in dim lighting) (Liu & Ostadabbas, 2017).

Radiofrequency identification (RFID) devices have also been suggested as a method for capturing data about healthcare activities. However, this method requires a receiver network created by a series of well-placed antennas, which can be obscured by areas with no reception (known as "dead spots") and require costly infrastructure upgrades (Shah & Fioranelli, 2019).

Some have endeavored to surmount these obstacles by developing a skeleton-free fall detection system using depth images combined with random decision tree forest (RDF). Foreground segmentation RDF has been used to recognize patient positioning. This approach involves training and evaluating RDF with synthetic datasets, while employing a support vector machine classification model to monitor changes in lying posture over time and detect falls (Abobakr et al., 2017). Notably, this method ensures patient privacy during surveillance. Implementing a similar model in real-world settings has the potential to revolutionize healthcare by alleviating the burden on healthcare workers tasked with patient monitoring. Similarly, the AUGi device adopts a comparable approach but integrates nursing data by incorporating identifying beacons on nurses. This enables the collection of nurse-related data, such as identifying which nurse is attending to a patient, without compromising patient anonymity.

Therefore, the purpose of this study was to use data generated by this novel technology with the ability to capture bedside interactions, to characterize nurse surveillance including the frequency and duration of BSR and HR and other nurse interactions at the bedside, 24 h/day, 7 days/week for 1 year. This study ended because of the onset of the COVID-19 pandemic but allows for useful comparison data to detect how and whether the pandemic has caused lasting changes in the way nurses practice and the amount of time spent with patients.

METHODS

Validation of the technology

The AUGi device was piloted on the same units as the study to ensure that (1) the AUGi device could collect the required data, and (2) the variables requested from the AUGi device would be reported by Inspiren to the research team in a useable format for further analysis. Computer vision was utilized to detect the presence of a patient in the bed; however, it did not monitor patient identity and no dedicated beacon was positioned on the patient. The device uses a combination of Bluetooth Low Energy (BLE) beacon and computer vision to identify both the presence and identity of staff in the "bed zone." In addition, during the piloting of the device, the research team completed on-site manual validation of the data provided by Inspiren to ensure its accuracy through direct observation. Data collected by the AUGi device were stored in the Amazon cloud as comma-separated values (CSV) and then imported directly into SAS. After importing into data analysis software, data were aggregated to represent event-contingent data (rather than continuous or repeated data) variables to extract data such as BSR by nurses, HR by nurses, frequency of nurse interactions with patients, and other interactions at each bed from the AUGi device. We also created predictor variables 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 AUGi device at each bed on each shift. From this bed shift level data, we generated descriptive statistics on nurse interactions at the bedside (such as frequency, duration total time spent with nurses) (Sun et al., 2021). At this facility, patients shared rooms, and beds were divided by curtains; therefore, we only tracked the activity at the bedside (not when the nurse was in other areas of the room as they may have been with other patients). Previous literature has emphasized that all activities of the nurse that allow for observation of the patient have a cumulative effect over time; therefore, we incorporated all interactions with the patient at the bedside regardless of the primary intent of the interaction (Kutney-Lee et al., 2009).

Devices were installed and operational 1 month prior to the start of the study; during this period, functional testing was performed on the devices and system daily. The team would physically test the performance of beacon capture in each room and call bell activations by logging into the system remotely as well as within the mobile application and assessing whether the system registered interactions accurately and that what was happening in the room reflected what was being logged by the iN system. This assured that the raw data streaming from the devices matched what was being reported on the application and that the timing matched the actual time of the event, both via what was observed in-person and remotely.

Each base station was configured per room; there were several different types of configurations, including one bed, two to three bedrooms, and five beds/room. We observed staff visit scenarios in each configuration and if inter-rater reliability was less than 100%, we adjusted the base station devices until each was capturing data optimally and there was 100% accuracy across all devices. At the start of data collection, two hospital managers performed user acceptance testing by running through nurse visit scenarios in each room and rated the reliability of the data collection versus the activities in the room; inter-rater reliability was 100% (Kappa = 1) (McHugh, 2012). Additionally, after all data were collected at the end of the study, we checked the data for internal consistency over time (i.e., outliers or inconsistencies in observations) and no discrepancies were noted.

During the first month of the study, one Inspiren employee was on site every day to answer questions from the staff, check that the devices were online, and ensure that there was no gap in timing between what was observed and what was reported via the mobile application. At all stages, device function was monitored remotely 24 h per day/7 days per week. Device diagnostics were streamed remotely to the Inspiren internal engineering and support team to monitor system health. Notifications of anomalies from the diagnostics were reported in real time (such as if a device was offline/unplugged) and needed to be actioned. In such cases, either an Inspiren employee was dispatched to rectify the problem, or the hospital IT staff were notified and dispatched to correct any problems.

In addition to visual and remote checks on the viability of devices and data, the iN devices were provisioned to the hospital WiFi network, such that it would not connect elsewhere (i.e., if the device were removed from the hospital room). Devices were secured with a safety lock so once locked into the baseplate, they could not be removed.

Design

After validating the technology, the AUGi devices were installed at 37 patient beds in two medical/surgical units (Table 1) at a large urban acute care hospital; 99 users were tracked, including managers, nurses, nurse attendants, and technicians. All patients staying on the units and nurses working on the units during the study period were included in the study. Data were collected from the beginning of the night shift of April 15, 2019 and to the end of the day shift of March 15, 2020. Nurses' time and activity at the bedside were characterized using the "AUGi" device. While the AUGi device captured all movement in the area of the patient bed, the beacon was used to identify or "tag" nurses as they moved in and out of the patient

TABLE 1 Characteristics of units.

Unit type	Unit capacity	2019 ADC	RN staff	Years of service	BSN rate	Cert rate	Description
Med/Surg	21	19.09	20	7.25	84%	20%	Telemetry/medical patients, CHF, COPD, Neuro, stroke, pneumonia, asthma, angina, renal, cardiac, and pulmonary disease
Med/Surg	16	14.59	15	3.47	100%	20%	General medical patients such as renal, podiatry, and diabetic patients

Abbreviations: ADC, average daily patient census; BSN rate, percent of nurses with a bachelor's degree in Nursing; Cert rate, percent of certified nurses; Years of Service = average years of service per nurse.

TABLE 2 Descriptive stats (mean, SD, median, etc.) for all interactions (including HR, BSR) × day/night.

	Nursing interaction with patients at the bedside in seconds			
	Day shift (DS), $n = 247{,}243$	Night shift (NS), $n = 161{,}315$	Total, $N = 408{,}588$	Difference between DS and NS
Mean	70.33	73.66	71.64	3.34 s NS < DS* ($p < 0.0001$)
Std deviation	97.79	105.60	100.97	
Variance	9563	11,152	10,193	
Median	34.33	35.03	35.00	
Mode	9.00	10.00	9.00	
Range	1786	1771	1786	
Interquartile Range	65.66	69.89	67.29	

Note: Interactions were excluded if they were shorter than 7 s and longer than 30 min. Interactions $N = 408{,}588$ from 37 beds and 49 nurse users over 670 shifts. Average 7.86 interactions per bed/shift. Average total interaction time 9.39 min/bed/shift.

*Significant at the $p = 0.05$ level with 95% confidence.

room. Data were aggregated to represent event-contingent data (rather than continuous or repeated data) variables to extract data such as BSR (a simultaneous interaction of two nurses from different shifts at the patient bed in the hour before or after a shift change (from 06:00 to 07:59)) by nurses, HR by nurses (the first nurse–patient interaction detected per bed during a given hour), frequency of nurse interactions with patients, and other interactions at each bed from the device, as described above.

We assumed that the data captured by the AUGi devices were comprehensive over the time period in which they were deployed; therefore, we interpreted any periods with no activity detected as periods of no nurse–patient interactions. Relatedly, if there were no interactions detected at a bed for the duration of a shift, we defined the bed as unoccupied for that shift. Descriptive statistical analyses for duration of BSR, HR, and other nurse–patient interactions were conducted. Because the data were not normally distributed, a Mann–Whitney *U*-test comparing mean interaction times between day and night shifts was calculated. A Chi-square test was used to detect whether there were significant differences in the completion of BSR or HR between day and night shifts. RStudio (Rstudio Team, 2020) and SAS software (SAS Institute, Cary, NC) were used to analyze these data. These devices were installed for non-research purposes and data were de-identified before the research team accessed them; the research team had no direct access to patient or nursing staff data. When data are de-identified, they are no longer considered human subjects; therefore, consent was not required. The study was approved by the Columbia University Irving Medical Center, NewYork-Presbyterian Queens Hospital, Weill Cornell Medical College, and The City University of New York Institutional Review Boards (IRB File #2020-0035) as exempt.

RESULTS

AUGi captured all activity at the patient's bedside for 12 months. The two units had a combined average daily patient census of 16.84, 17.5 nurses on staff, 5.36 years of service, 92% of nurses held a Bachelor of Science in Nursing (BSN), and a 20% certification rate (Table 1). 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 nurse's mean interaction time with a patient was 3.34 s 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 s shorter than

TABLE 3 Percentage of number of times bedside shift report or hourly rounding were completed *N* (%).

	Day shift, *n* (%)	Night shift, *n* (%)	Total *N* (%)
Bedside shift report	2289 (19.74)*	2345 (21.68)*	4634 (20.68)
Hourly rounding	83,842 (60.25)*	58,551 (45.11)*	142,393 (52.94)

Note: 90.4% occupancy rate of beds (range from 76% to 97%) of shifts.
*A significant difference at the $p=0.05$ level.

night shift, which was statistically significant (standard deviation [SD] = 0.32, $p<0.001$). However, nurses spent more time in total with patients on the day shift.

For each nurse, mean number of interactions per bed was 7.86 (SD = 10.13); the mean total time of interactions per bed was 9.39 min (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 on the day shift 19.74% of the time ($n=2289$) versus 21.69% on the night shift ($X=0.0037$, $p<0.05$) (Table 3). HR was completed 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 ($X<0.00001$, $p<0.05$). The mean time per HR was 69.5 s (SD = 98.07) and 50.1 s (SD = 56.58) for BSR.

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 s (SD = 98.07) (Table 2) and 50.1 s (SD = 56.58) for BSR.

DISCUSSION

While our analysis indicates 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-h shift, on average, nurses visited the patient's bed 7.86 times. However, on average, the total time spent at the bedside was 10.62 min during the day and 8.02 during 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 night shift. 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 eight patients on the day shift and seven 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 (HR) 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.

Baseline data collected in another study indicated that 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 (Sun et al., 2021). Results from this study represent a 17.58% increase in HR. Additionally, our previous data indicated that BSR was only conducted on this site in 3% of the instances in which there was an opportunity to do so; data from this study demonstrate a 17.72% increase. These suggest that awareness of patient rounding and BSR either via app or the visual reminder of the device could increase patient surveillance by nurses. Future studies may illuminate these findings.

Overall, nurses had more than seven patients per shift and the total time spent with all patients per shift was 9.39 min on average, throughout 12 h. Previous studies have suggested a far higher amount of time that nurses spent at the bedside—some as much as 37% of their shift. 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 min at the bedside, per patient per 12-h 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 HR 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 of 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 (Wallace, 2018). However, because of the way these data were 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 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 h/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 BSR and HR) have an effect on patient outcomes. Data collected from this study will be 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.

Limitations

This study relies on a device to detect human presence using Bluetooth and computer vision. Although they were extensively tested, it is possible that certain positions of either the patient or the clinician did not allow for detection, and this did not account for times where the patient was not in the bed (e.g., ambulating in the hallway, in the bathroom, etc.). Moreover, being able to detect instances of BSR and HR does not fully capture the quality or content of those interactions, and the calculation method for percentages of BSR and particularly HR completed may have undercounted in cases where patients only partially occupy their beds during shifts (e.g., if they are away from their beds for testing or procedures mid-shift). More data will be needed from other types of units to determine the generalizability of this study; however, this provides evidence that could be generalizable to similar types of units and settings.

This hospital was at the epicenter of the COVID-19 pandemic in Queens, New York; therefore, the study was put on hold as of March 15, 2020. For this reason, we were also delayed in gathering other correlative data, and so analyses were also delayed. However, this provides interesting pre-pandemic information that could be compared with similar data in the future to assess whether the pandemic has led to lasting changes in the way nurses perform their jobs. It is conceivable that nurses have even less time with patients given the worsening nursing shortage.

Future studies

Currently, we are installing this device in assisted living facilities; the device includes the option to alert the nurse if it detects that the patient is getting out of bed, about to fall, or falling. We will describe interactions within this setting, as well as whether the device is capable of reducing falls in assisted living facilities, where there are fewer direct care interactions. Future studies could incorporate qualitative information to elucidate the potential interpretation and impact of findings, as well as additional areas for further investigation.

CONCLUSIONS

The aim of this study was to better understand nursing interactions at the bedside. Historically, researchers have used several methods to capture valuable healthcare interactions, including radiofrequency identification (RFID) devices and direct observation. However, methods like RFID are only as effective as the receiver network created by a series of well-placed antennas, which can be plagued by areas with no reception. Because the AUGi devices sat at the head of each bed connectivity was not an issue. The analytical advantage of these data captured by AUGi was the lack of sampling bias which is a risk with direct observation. The devices in this study continuously monitored the bedside, capturing patient movement and bedside interactions.

To our knowledge, this is the first study to provide continuous surveillance of nurse activities at the bedside over a year long period, 24 h/day, 7 days/week. We detected nurses spend less than 1 min giving report at the bedside, and this is only completed about 20.7% of the time. HR was completed only 52.9% of the time. Additionally, nurses covered more than seven patients per shift and spent only 9 min total with each patient. Further study is needed to detect whether there is an optimal timing or duration of interactions to improve patient outcomes. In the future, such technology may allow nurses to cluster visits for optimal timing and duration of patient interactions.

CLINICAL RESOURCES

Bedside shift report has been suggested as a means of reducing patient falls. The AHRQ has provided the following resource to improve nursing compliance with this strategy: https://www.ahrq.gov/sites/default/files/wysiwyg/professionals/systems/hospital/engagingfamilies/strategy3/Strat3_Implement_Hndbook_508.pdf.

ACKNOWLEDGMENTS

The authors would like to acknowledge Dr. Alan Levin for his assistance in navigating the study site and Jeffery Morelli for his assistance in extracting the AUGi data.

FUNDING INFORMATION

This study was funded by The Agency for Healthcare Research and Quality (AHRQ), R03 HS27006-01A1 IMProving Outcomes Related to Patients Through Advanced Nursing Technology (IMPORTANT). The AHRQ had no role in this study.

CONFLICT OF INTEREST STATEMENT

We have no conflicts of interest to disclose.

DATA AVAILABILITY STATEMENT

Due to the sensitive nature of hospital data, supporting data are not available.

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How to cite this article: Sun, C., Fu, C. & Cato, K. (2024). Characterizing nursing time with patients using computer vision. *Journal of Nursing Scholarship*, *00*, 1–7. https://doi.org/10.1111/jnu.12971