Enhancing Nurse Rounding Performance and Patient Satisfaction using Real Time Location System

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ABSTRACT

The ongoing healthcare workforce crisis, exacerbated by the Great Resignation, led to a substantial reduction in available personnel, including a 30% decline in nursing staff. This shortage can lead to longer patient wait times and compromised patient safety, contributing to more medical errors and higher mortality rates. A key factor contributing to nurse attrition is burnout, often driven by excessive administrative burdens. One effective strategy to mitigate burnout and reduce turnover is improving job satisfaction by minimizing administrative workload, thereby enabling nurses to dedicate more time to direct patient care. Additionally, high-quality patient rounding is essential for enhancing Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) scores, which assesses patient perceptions of hospital experiences. These scores inform quality improvement initiatives, promote transparency, and influence reimbursement under value-based purchasing programs.

Real-Time Location Systems (RTLS) have emerged as a transformative technology in healthcare, providing enhanced visibility and operational efficiency for both clinical and administrative workflows. By leveraging real-time location data, RTLS enables continuous monitoring of nursing staff movements, reduced response times to patient needs, and efficient personnel management.

This study examines the implementation of RTLS in a large community hospital, integrating RFID-enabled badges into nurse rounding protocols. To establish a data-driven correlation between rounding practices and patient satisfaction, a decision tree machine learning model was developed. This model generates interpretable, rule-based insights that quantify the impact of rounding on HCAHPS scores. By leveraging these insights, nursing teams enhanced the consistency and effectiveness of patient interactions, leading to measurable improvements in patient satisfaction.

This research underscores the potential of RTLS to model hospital system efficiency, automating insights to optimize resource allocation and improve patient care outcomes. By integrating real-time monitoring with predictive analytics, hospitals can enhance operational efficiency while pushing a more positive healthcare experience for both patients and staff.

ABOUT THE AUTHORS

Shuxin Li is a lead Data Scientist at AdventHealth with over a decade of experience in healthcare analytics and advanced machine learning applications. She holds a Master of Science in Computer Science from the University of Central Florida at AdventHealth, Shuxin specializes in clinical data science, predictive modeling, and real-time analytics to improve patient care and operational efficiency. Her recent work includes leveraging Real-Time Location Systems (RTLS) and decision tree models to enhance nurse rounding and patient satisfaction.

Alyssa Tanaka, Ph.D. is the Director for AI Innovation for AdventHealth, where she oversees the strategy and execution of AI research and development efforts within the hospital system. Prior to joining AdventHealth, she worked as a Scientist within the Defense sector, applying AI approaches to enhance the medical care of warfighters. The focus of her research has centered around clinical decision support and trust in AI. She received her Ph.D. in Modeling and Simulation from The University of Central Florida.

Lucy Ha is an undergraduate student at the University of Florida pursuing a Bachelor of Science in Data Science with minors in Women's Studies and Mathematics. Her academic focus includes geospatial analysis, data-driven healthcare research, and machine learning applications. She has contributed to interdisciplinary projects in both environmental modeling and healthcare innovation, including her work on flood mapping using Google Earth Engine and her recent involvement in enhancing nurse rounding practices through real-time location system (RTLS) data integration. Lucy is particularly interested in using data science to drive social impact, improve system efficiency, and inform equitable decision-making.

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INTRODUCTION

As healthcare systems navigate increasing complexity—marked by nurse staffing shortages, rising patient acuity, and growing demands for quality care—ensuring operational efficiency and patient satisfaction has become a top priority for hospitals and clinical leadership. Inefficient or inconsistent nurse workflows can result in missed rounds, delayed responses to patient needs, and reduced engagement, all of which negatively impact patient experiences and outcomes (Roper et al., 2015). Traditional workflow evaluations, often dependent on manual documentation and retrospective audits, fall short in providing the real-time, objective insight needed to address these challenges effectively.

To overcome these limitations, AdventHealth Celebration deployed a Real-Time Location System (RTLS) to model and improve nursing workflows—specifically focusing on nurse rounding practices. RTLS technologies, powered by Bluetooth Low Energy and Wi-Fi, offer granular, continuous tracking of staff movement and interactions within the hospital environment (Yoo et al., 2018). This real-time visibility enables organizations to analyze workflow patterns, detect inefficiencies, and measure adherence to best practices in a systematic and scalable manner.

By integrating RTLS data with Press Ganey patient satisfaction survey results, AdventHealth Celebration developed a set of interpretable, actionable rules that helped nursing staff enhance the consistency, quality, and timing of patient interactions. These insights empowered the care team to optimize their rounding behaviors, address gaps in service delivery, and align more closely with patients' expectations and needs.

The implementation of RTLS not only provided an objective lens into day-to-day nursing operations but also supported the creation of a closed-loop feedback system—where data-driven insights informed rounding schedules, patient assignments, and overall care strategies. This evidence-based approach has enabled the hospital to make more informed decisions regarding process improvement, ultimately resulting in improved staff workflow, higher HCAHPS scores, and more meaningful nurse-patient engagement.

RTLS Implementation

RTLS represent a transformative technology within the hospital environment, enabling precise, real-time tracking of assets, equipment, and clinical personnel within the hospital environment. The core value of RTLS lies in its ability to continuously capture the location of tagged entities, providing organizations with enhanced operational visibility and the data needed to drive informed, evidence-based decisions.

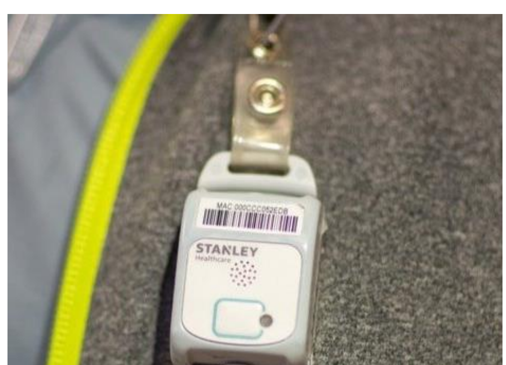

Figure 1. RTLS-enabled badge

The RTLS infrastructure deployed at AdventHealth is built upon Ultra-Wideband (UWB) technology, which transmits short-duration signals from wearable tags (Figure 1) to strategically positioned anchors (also known as readers or receivers). These signals are captured and processed by an integrated software platform, which calculates spatial coordinates and renders movement data through advanced visualization and analytics tools (Trebuňa et al., 2023).

In healthcare settings, RTLS implementations often combine various technologies, each tailored to specific use cases and environmental conditions. Commonly used modalities include Radio Frequency Identification (RFID), Wi-Fi, UWB, and Bluetooth Low Energy (BLE):

- RFID offers a cost-effective solution for scenarios where line-of-sight tracking is not required (Kuipers et al., 2014; Hakim et al., 2006).
- Wi-Fi-based RTLS leverages existing wireless infrastructure, enabling seamless integration and broad coverage throughout medical facilities.
- UWB is particularly well-suited for high-precision indoor tracking, capable of delivering sub-meter accuracy in complex or cluttered environments.
- BLE is valued for its low energy consumption and compatibility with mobile devices, making it ideal for patient-centered applications (Hakim et al., 2006).

RTLS tags were deployed to 1,332 staff members at AdventHealth Celebration, enabling continuous monitoring of nurse location and movement. Anchors installed throughout the care environment collected these signals and transmitted the data to a central analytics platform. The system employed robust algorithms to calculate positioning in real time, supporting interactive dashboards and workflow visualizations that inform both operational decision-making and care delivery strategies (Yoo et al., 2018). Figure 2 visually depicts the movement data generated by RTLS.

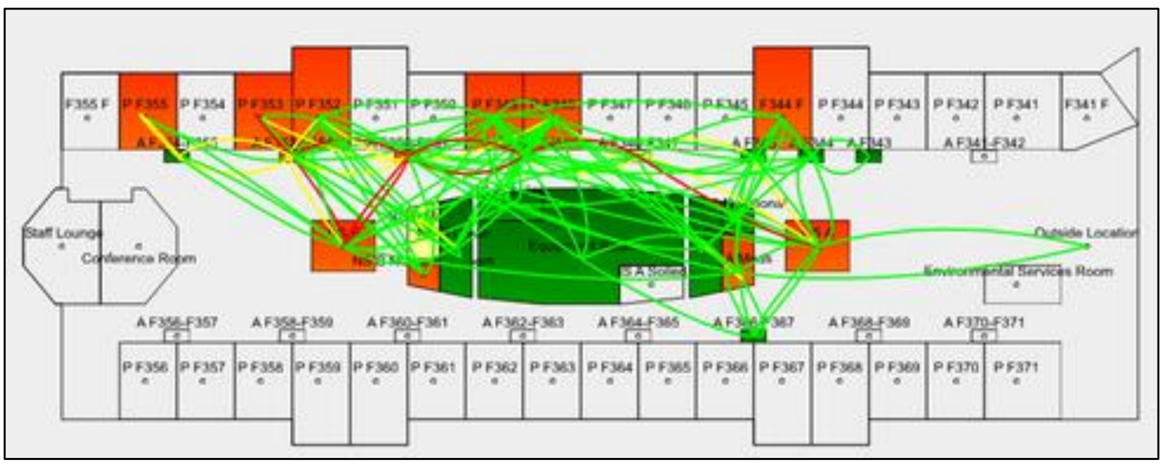

Figure 2. A spaghetti diagram visualizes the flow of a RTLS nurse activity

RTLS introduces a data-driven approach to nurse rounding by enabling objective measurement of staff movement and patient interaction. RTLS tags assigned to nurses facilitate real-time tracking of rounding frequency, duration, and consistency. This continuous data stream supports the development of performance dashboards that highlight adherence to rounding protocols, identify areas for improvement, and provide targeted feedback to nursing staff. When integrated with a decision tree model, RTLS data further enhances the ability to optimize rounding strategies, tailor care to patient needs, and ultimately improve the efficiency and effectiveness of nursing workflows.

METHODS

The Press Ganey HCAHPS surveys were administered during the same time period as the RTLS data collection. Patients were unaware of the RTLS tags worn by staff. Each patient survey could be linked to their specific encounter ID, which includes details such as admission and discharge dates and inpatient room numbers, enabling accurate correlation between satisfaction data and staff-patient interactions.

An Association Rules machine learning (ML) analysis was used to identify key factors correlated with patient satisfaction as measured by HCAHPS scores. The primary objective was to evaluate whether staff and leader rounding behaviors were significantly associated with both positive and negative patient ratings, thereby providing an objective confirmation of anecdotal and observational assumptions. Positive, negative, and mixed ratings were developed by aggregating individual responses into a composite satisfaction rating for each patient visit (Figure 3).

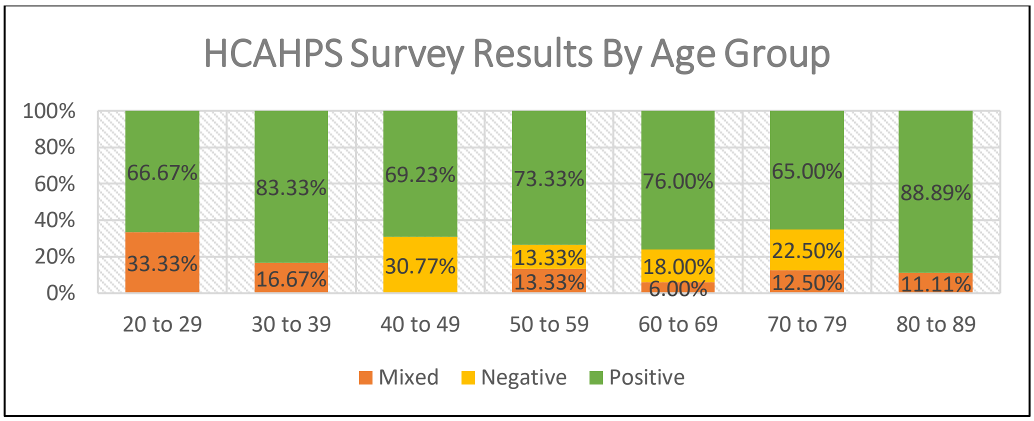

Figure 3. HCAHPS Survey Results sorted by age groups

In this network graph, nodes represent categorical variables such as age group, unit type, and rounding behavior, while edges indicate associations derived from the algorithm. The proximity and connectivity of nodes reveal the strength and frequency of co-occurrence among variables (Figure 4).

Notably, "Staff Rounding" and "Leader Rounding" appear prominently in the central cluster of the diagram, indicating a strong association with patient satisfaction scores. Their central location and high node degree suggest that these behaviors are frequently linked, either positively or negatively, with other variables impacting HCAHPS outcomes. This supports the hypothesis that consistent and meaningful rounding practices are influential drivers of the patient experience.

High-quality patient rounding is defined as maintaining a nurse rounding compliance rate between 90% and 100%. This range ensures consistent patient check-ins, supports safety, and balances staff workload. Rounding below 90% can lead to delayed care, reduced patient satisfaction, increased call light usage, and higher risk of adverse events. Conversely, exceeding 100% may signal inefficiencies such as over-reporting or redundant documentation, potentially leading to nurse fatigue and reduced patient engagement. Purposeful rounding, therefore, aims to optimize both frequency and quality of interactions.

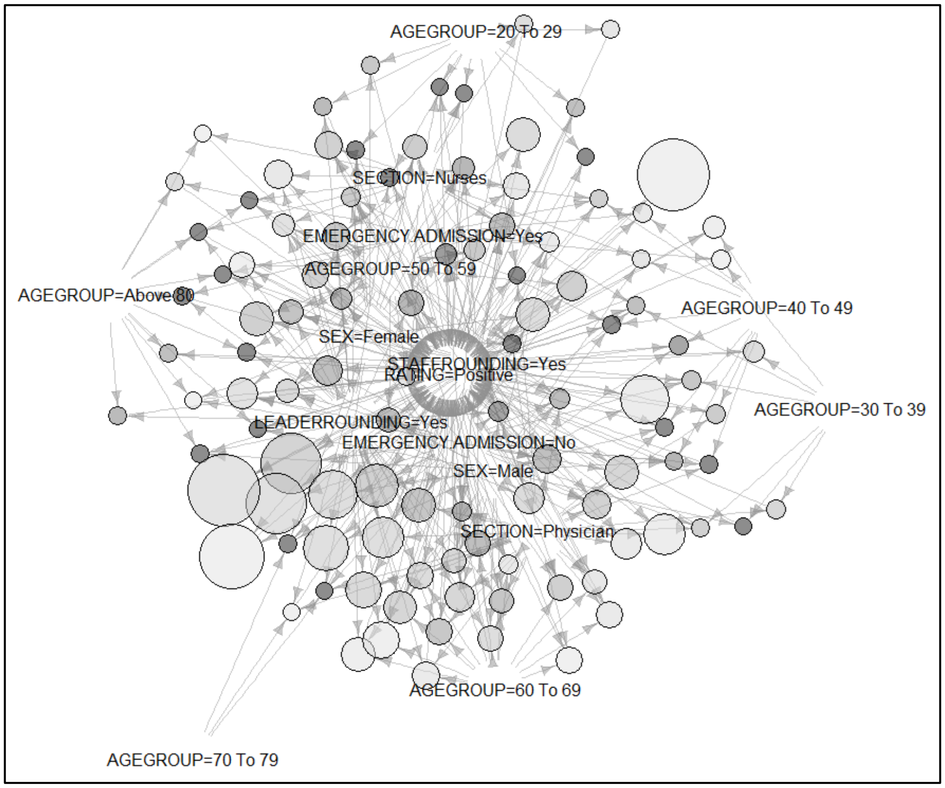

Figure 4. Association Rule Model shows the relationship between staff rounding vs patient rating

After using Association Rules analysis to identify factors most strongly correlated with HCAHPS patient satisfaction scores, these findings were integrated with RTLS-derived rounding data to construct a predictive model (Figure 5). The resulting decision tree provides a transparent and interpretable framework for guiding clinical operations, specifically offering actionable strategies to improve patient experience based on actual staff activity patterns. The decision tree model was chosen for its interpretability, as it allows for straightforward visualization and comprehension, making it accessible to both technical and non-technical stakeholders. Additionally, decision trees effectively capture non-linear relationships, enabling the identification of complex patterns between patient rounding practices and their impact on patient satisfaction scores.

The model draws on several integrated data sources:

- RTLS movement data captured detailed, time-stamped information on the location, duration, and frequency of nurse-patient interactions.
- Patient satisfaction data were collected through standardized HCAHPS surveys administered via Press Ganey, which provided the dependent variable used to train the model.
- Additional contextual data, such as staff shift details (e.g., day vs. night shift), were also included to assess variation in rounding behavior across timeframes.

Each data stream contributed a distinct analytic value to the model. RTLS data ensured an objective, real-time representation of nursing behavior, overcoming the limitations of self-reported documentation. HCAHPS scores, as validated indicators of care quality, allowed the model to identify behavior patterns linked to patient perception. Shift-level variables further refined the model by differentiating between the constraints and opportunities of day and night workflows, enabling targeted insight.

The evaluation revealed that night shift rounding performance was the most influential predictor of patient satisfaction. Specifically, when night shift rounding met or exceeded 70% compliance with the expected 2-hour rounding interval, the model predicted a 59% probability of achieving a positive HCAHPS score; however, the likelihood of a positive rating dropped substantially (approximately 41%) when this benchmark was not met, suggesting that lapses in night rounding frequency are closely associated with diminished patient experience.

Figure 5. Decision Tree Model shows the relationship between staff member's shift, rounding, and patient rating

Within this lower-performing subgroup, day shift rounding duration emerged as a critical secondary factor. The model identified that when nurses spent at least 3.9 minutes per patient during day shift rounds, the likelihood of receiving a positive HCAHPS score increased by an additional 18%, restoring performance to levels comparable to compliant night shift conditions. Conversely, if both night shift rounding frequency and day shift rounding duration fell below their respective thresholds, the probability of achieving a positive patient satisfaction rating declined significantly, reinforcing the compounding impact of suboptimal performance across shifts.

Through this decision tree model, the team established an evidence-based framework for translating staff movement and behavior data into practical guidelines that can support clinical decision-making, improve workflow adherence, and ultimately elevate the quality of the patient care experience.

RESULTS

The implementation of RTLS and the associated operational workflows enabled the hospital to achieve a critical outcome: improved adherence to the hourly nurse rounding protocol. Post-adoption of RTLS, clinical units reported approximately 90% compliance with the policy requiring nurse-patient interaction for dayshift and night shift (at least once per hour and once per two hours respectively). The system also supported the broader adoption of purposeful rounding, an approach that emphasizes structured, intentional engagement between nursing staff and patients to enhance care quality and patient experience.

Upon deployment of RTLS in late 2022, including enhanced nurse rounding workflows and real-time monitoring of patient-staff interactions, the year-over-year trend in patient satisfaction scores from the Consumer Assessment of Healthcare Providers and Systems (CAHPS) reflects an upward trajectory in patient experience ratings. By 2024, the hospital achieved a CAHPS top-box score of 82.46%, positioning it in the 83rd percentile nationally (Figure 6). This trend suggests that the integration of RTLS technology and evidence-based rounding protocols may have contributed significantly to improved patient satisfaction and care delivery, highlighting the value of operational analytics in driving clinical performance.

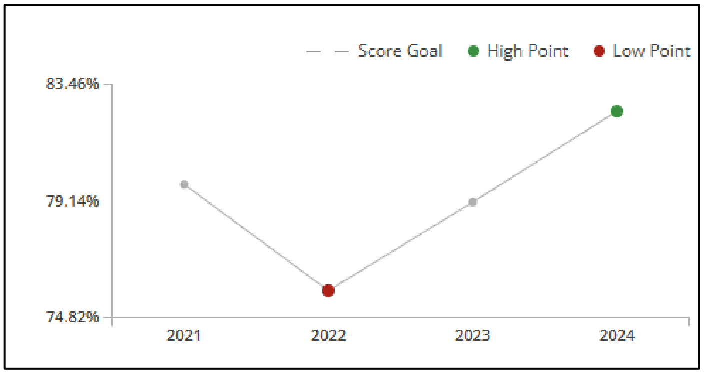

Figure 6. Consumer Assessment of Healthcare Providers and Systems (CAHPS) trend between 2021 and 2024

Table 1 summarizes the performance of key HCAHPS survey measures comparing the periods pre- and post-implementation of the RTLS across several domains, including *Global Items*, *Communication with Nurses*, and *Response of Hospital Staff*. Positive improvements were observed across all measured items, with the most substantial gain observed in the item *"Help toileting soon as you wanted"*, which increased by 5.16 percentage points. Other significant improvements include *"Rate hospital 0–10"* (+3.37%) and *"Nurses listen carefully to you"* (+1.74%). The percentage of patients reporting nurses treat them with courtesy and respect remains high, increasing slightly from 88.38% to 89.02%. Overall, the data indicate consistent and incremental improvements in patient satisfaction, particularly in areas related to nurse communication and responsiveness, suggesting that operational changes—such as enhanced rounding protocols—may be contributing to better patient experiences.

Table 1. Individual HCAHPS scoring impact Pre- and Post-implementation

Domains	Items	N	Post-Implementation	Pre-Implementation	Change
Global Items	Rate hospital 0-10	2845	82.46%	79.09%	3.37%
Global Items	Recommend the hospital	2847	83.85%	82.79%	1.06%
Communication	Nurses treat with courtesy/respect	2852	89.02%	88.38%	0.64%
Communication	Nurses listen carefully to you	2849	81.47%	79.73%	1.74%
Communication	Nurses explain way you understand	2843	70.86%	70.81%	0.05%
Hospital Response	Call button help soon as wanted it	2893	64.32%	63.13%	1.19%
Hospital Response	Help toileting soon as you wanted	1282	66.61%	61.45%	5.16%

In addition to improvements in patient experience scores, a secondary outcome was a reduction in registered nurse attrition rates. As RTLS adoption provided more structured and data-informed approaches to nurse rounding, the emphasis on purposeful and efficient patient interactions increased. This operational alignment likely contributed to improved workplace satisfaction and retention. As a result, the annual separation rate for registered nurses declined to approximately 8.5%, representing a meaningful reduction in turnover.

CONCLUSION

This paper has presented an integrated, data-driven approach to improving nurse rounding practices and patient satisfaction through the implementation of RTLS and decision tree modeling within the healthcare domain. By leveraging RTLS data in conjunction with machine learning, the organization gained meaningful insights into the behavioral patterns and operational factors that influence patient experience, enabling the development of targeted and actionable strategies to enhance care delivery.

The use of RTLS allowed for objective, real-time monitoring of nurse rounding behavior, which was then analyzed using decision tree models to identify key predictors of positive HCAHPS scores. These insights were translated into practical rounding guidelines, supporting staff in delivering more consistent and purposeful patient interactions. Over the years following implementation, patient satisfaction scores have improved consistently, indicating sustained performance gains as staff became increasingly proficient in applying data-informed rounding protocols.

In addition to elevating the patient experience, the initiative produced valuable operational benefits, including enhanced situational awareness and the ability to rapidly locate nursing personnel during critical clinical events, improving response times and care coordination. A reduction in registered nurse attrition was also observed, suggesting that the initiative contributed not only to patient-centered outcomes, but also to a more stable and engaged nursing workforce. This likely driven by clearer workflows, reduced ambiguity in rounding expectations, and targeted efficiency gains post-RTLS implementation (Figure 7). The healthcare sector has experienced workforce losses of approximately 20%, including 30% of its nursing staff, largely due to job burnout. The improvement of operational efficiency through structured workflows can play a critical role in reducing attrition by alleviating stress and enhancing staff support.

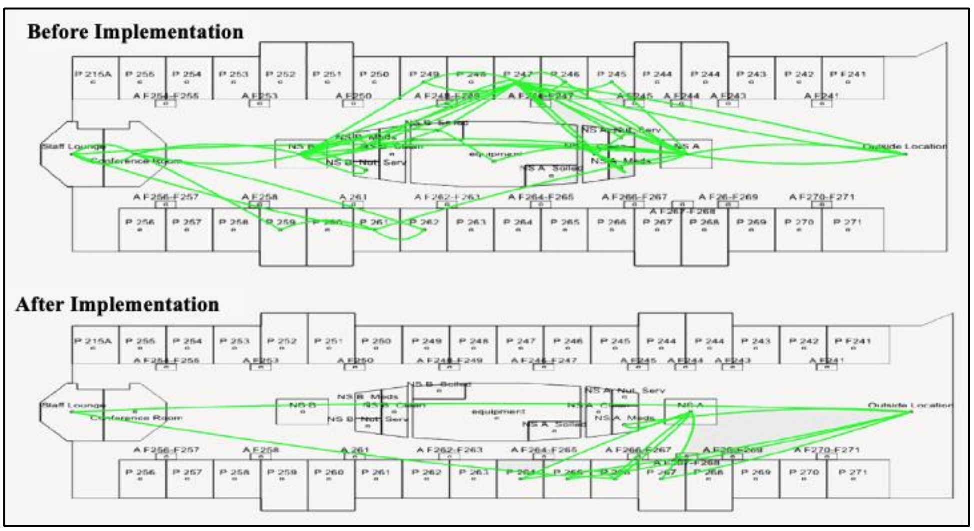

Figure 7. Depiction of nurse movements within a unit pre- and post-implementation

Furthermore, this work illustrates the broader potential of combining artificial intelligence and clinical decision support tools to extend beyond traditional capabilities. By embedding intelligent, adaptive systems into daily operations, healthcare organizations can continuously refine practices, support learning health systems, and make better-informed decisions that align with both patient and staff needs.

Beyond healthcare, RTLS technologies have significant applications in military, defense, and logistics settings. In military operations, RTLS can track troop movements, monitor equipment usage, and enhance situational awareness through real-time visibility. Base security can be improved by monitoring personnel and vehicle movements with alert systems for unauthorized access. In logistics, RTLS supports supply chain tracking of assets like ammunition and medical supplies across transport modes, ensuring delivery and cold chain compliance. This technology is also relevant in maintaining readiness on aircraft carriers, where “rounds” performed by maintainers mirror healthcare rounding protocols, ensuring task completion in closed network environments.

Looking ahead, real-time tracking systems can support a dynamic mission-aware supply chain that reprioritizes deliveries based on live battlefield conditions. Automated convoy visibility systems could use RTLS data to monitor vehicle spacing and trigger threat response actions. Cold chain assurance for battlefield medications ensures viability of sensitive medical supplies in forward zones. RTLS-integrated smart depots may pre-position critical equipment by predicting operational needs using real-time patterns. Personnel tracking in expeditionary units would help measure deployment efficiency and field setup times. In tactical air delivery, RTLS-enabled bundles can broadcast locations post-drop to facilitate rapid recovery. Furthermore, anomaly detection based on learned movement patterns can help mitigate insider threats and unauthorized asset use. Together, these advancements highlight how military and logistics operations can adopt healthcare-inspired RTLS frameworks to optimize resource use, enhance safety, and maintain operational superiority.

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