Assessing the Potential of Technology to Describe Resident and Staff Interactions in Assisted Living Facilities

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ABSTRACT

PURPOSE: Falls are a significant financial burden and health hazard for residents in assisted living facilities (ALFs). However, limited capacity to observe residents has hindered understanding of resident–staff interactions within rooms. The current study aimed to describe nurse–resident interactions using data from a remote technology combining computer vision and staff location tracking.

METHOD: Eighty-three staff working at an urban ALF with 215 residents were trained at the initiation of the study. Remote surveillance devices were installed in 32 residences and staff and resident interactions were tracked over 170 days.

RESULTS: Staff visited residents an average of 20.7 times per day for short durations (mean = 1.08 minutes). Urgent alert response times averaged 3.0 minutes, with faster response times through the mobile application (mean = 2.7 minutes) compared to in-person (mean = 3.3 minutes) response.

CONCLUSION: By better understanding staff activity patterns in ALFs, this study has the potential to improve fall prevention and care for residents in ALFs. [*Journal of Gerontological Nursing, 50*(7), 7-11.]

Approximately $50 billion are spent annually on non-fatal falls in the United States, with this number expected to grow as the population ages (Florence et al., 2018). A significant portion of this cost stems from falls in assisted living facilities (ALFs), where residents with potentially lower mobility are more susceptible to falls and resultant injuries. More than 1 million older adults reside in ALFs in the United States; this number is expected to grow to >6.5 million people by the year 2030 (American Health Care Association, 2020). Falls in ALFs are difficult to ascertain because of uncertain documentation and overall lack of surveillance (Agency for Healthcare Research and Quality [AHRQ], 2019).

Between 2007 and 2016, the rate of death from falls increased >30% (Burns & Kakara, 2018), making fall prevention critical. Practices, such as bedside shift report (i.e., nurses giving report at the bedside with the patient and/or family present) and hourly rounding (i.e., having the nurse check on the patient hourly), are among methods suggested to decrease falls by increasing nurse (RN)–patient interaction (Hutchinson et al., 2017; Walsh et al., 2018). However, implementing these tasks can be cost-prohibitive and there is a lack of strong evidence regarding their effectiveness (Mardis et al., 2016). Furthermore, in facilities such as ALFs, where residents may be unmonitored for several hours (e.g., at night while sleeping), hourly rounding may be impractical. Yet, prompt evaluation of residents and circumstances leading to a fall are crucial for future prevention (AHRQ, 2017).

Current care plans in ALFs prioritize safety but lack real-time monitoring capabilities of hospitals (e.g., vital sign monitoring). This lack of real-time monitoring necessitates that ALFs use preventive strategies over relying on frequent rounding. Studies have shown limited effectiveness of hourly rounding in reducing falls,

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Figure 1. Beacon (left) is attached to staff badge to allow for monitoring interactions between staff and residents and wall-mounted hardware base station (right).

particularly due to cost and staffing limitations (Mardis et al., 2016). Historically, the invasive nature of methods such as video surveillance has prevented in-depth monitoring of patient rooms and did not provide information on staff behavior (Berridge et al., 2019). Use of smart cameras that obfuscate patient identity and maintain privacy are critical developments in electronic surveillance and could allow for early detection and prevention of patient falls (Sapci & Sapci, 2019).

Electronic surveillance allows for proactive adjustments to resident care plans. Regular fall risk assessments, which identify changes in resident's mobility or cognitive function, can help anticipate potential falls (Deandrea et al., 2013). These assessments can then inform adjustments to care plans, such as increased assistance with transfers or environmental modifications (Racey et al., 2021). This proactive approach allows for targeted interventions before a fall occurs, ensuring resident safety and potentially reducing the need for frequent rounding.

ALFs currently lack technological solutions that support clinical decision-making based on staff time spent with residents. This critical data gap hinders identification of subtle changes in resident behavior, which could inform proactive care planning and ultimately reduce fall risks. Traditional assessment methods in ALFs are often infrequent, and major care plan revisions are uncommon. However, infrequent assessments can miss early warning signs that only become evident after a fall triggers a reactive reevaluation of care.

To increase patient surveillance, Inspir, an ALF in New York City, contracted with a company to pilot AUGi, a remote patient monitoring device that uses edge-artificial intelligence (AI; software built into the device rather than being run on other hardware elsewhere) to generate comprehensive data on in-room resident mobility, positioning, and interaction with clinicians. This technology-based intervention aimed to enhance resident safety by providing timely alerts to staff and enabling remote monitoring via a mobile application (app). Edge AI generates visual cues and notifications; that is, the technology integrates obfuscated computer vision and pose estimation to generate app notifications and a live video feed that allows staff to review the resident's position without exposing personal or identifying information. AUGi had not yet been studied in an ALF but successfully reduced falls in other settings (Sun et al., 2024; Sun et al., 2021). AUGi uses a combination of mounted hardware in the patient room (**Figure 1**), Bluetooth low energy (BLE) beacons worn by staff (**Figure 1**), and companion software supplied via mobile phone app that integrates these technologies. This novel method of data generation makes it possible to generate new knowledge about factors that influence patient outcomes.

Therefore, the purpose of the current descriptive study was to provide a comprehensive view of staff–resident interactions in an ALF over a 170-day period using secondary data collected by this technology. These objective data offer a significant advantage in understanding staff and resident behaviors in ALFs over traditional methods, such as camera use for surveillance, which imposes on patient privacy (Berridge et al., 2019) or subjective measures of interaction, which are incomplete (Rao et al., 2005).

This work builds on our previous research, which tested use of this equipment in the acute care setting (Sun et al., 2024; Sun et al., 2021). Although there have been increased use of cameras in ALFs for surveillance (Berridge et al., 2019), and other subjective measures of interactions within ALFs (Rao et al., 2005), to our knowledge this is the first comprehensive study of objective data in a real-life setting characterizing activities of residents and staff over a long period.

METHOD

Setting

An ALF with 215 residents in New York City was selected for the study. The ALF divides residents into different acuity levels: memory care, enhanced care, and assisted living. Memory care includes residents with dementia, Alzheimer's disease and related dementias; enhanced care provides higher acuity care for older adult residents unable to live independently; and assisted living comprises residents who need minimal assistance (e.g., meal preparation, weekly cleaning, help getting to health care appointments). The facility standard for staff (RNs and certified nursing assistants [CNAs]) working with residents ratio is 1:5 for memory care residents and 1:10 for other residents.

Population

Thirty-three devices were installed in 32 resident rooms of mixed type (memory care, enhanced care, and assisted living), and data were collected between September 19, 2022, and March 10, 2023. The study population primarily comprised older adults (average age = 85 years) with multiple chronic conditions. In the ALF, CNAs are the main care providers for residents, whereas RNs provide a more supervisory role. Therefore, we assigned RNs and CNAs individual BLE beacons after installation, with the understanding that the majority of interactions would be with CNAs. With the installation of the technology, 60 CNAs, 11 RNs, and 12 nurse managers were trained on the equipment and given beacons. Additional staff were trained with staff turnover so that the number of staff using the technology and assisting residents remained the same.

Technology

Testing was completed by ensuring staff BLE beacons were detected by the base stations located in the resident rooms, and the bed and chair zones in rooms were defined to ensure notifications would be generated based on patient activity (e.g., exiting the bed or chair). The facility designated which residents were considered a fall risk. Residents set in the app as a fall risk triggered an urgent "resident on floor," or non-urgent "out of bed" or "out of chair" notification based on their location within set zones.

Data Analysis

The base station locally identified when a resident was present in the room, analyzed resident pose, and published a time stamp of the resident's state (e.g., standing, sitting, lying) along with the specific room location (e.g., bed, chair, in room/out of view). These data were correlated with the staff beacon and pose estimation to determine staff visits. Data collected by the device were stored in the Amazon cloud as comma separated values (CSV). Data were aggregated to represent event-contingent variables (rather than continuous or repeated data) to extract data such as rounding by staff, frequency, and duration of staff interactions with residents, and other interactions at each bed from the AUGi device. From this aggregated bed shift level data, descriptive statistics on staff interactions at the bedside (frequency, duration, and total time spent with staff) were generated, outliers were removed, and averages were calculated.

Ethical Considerations

Because this was a secondary analysis of existing data, the Institutional Review Board deemed the study exempt. With the oversight of the authors, "Gemini" from Google AI was used to revise the manuscript and improve readability.

RESULTS

An overview of findings is provided in **Table 1**. During the 170 days, staff visited residents 112,818 times, which was 20.7 times per day per resident. Average visits were 1.08 minutes per resident. Removing outliers, 127 urgent alerts (resident on the floor) were sent (0.06/patient/day). Average response time to a non-urgent alert was 8.57 minutes overall; of these, the average staff response via the app (i.e., they opened the app on their phone and chose to resolve it remotely) was 8.57 minutes, and average in-person response time was 6.38 minutes. For urgent alerts, average response time was 3.3 minutes in person and 2.7 minutes in the app. A total of 1,880.3 staff care hours were spent in resident rooms (20.74 minutes/resident/room/day) for any reason. Residents were visited by staff 175,178 times (32.2 times/resident/day); of those visits 62,360 were done using the app (11.46 times per resident/day).

DISCUSSION

Implementing technology that continuously monitors resident behavior and staff interactions has the potential to be a powerful solution for improving patient safety. By providing insights into a resident's baseline activity patterns and detecting deviations, this technology can empower ALFs to proactively plan and prevent safety incidents. In addition, this technology allows for ongoing care plan updates based on real-time data, ensuring resident safety and well-being.

We found that providers in an ALF spend 20.74 minutes/patient/room/day and visited patients 20.7 times per day (an average duration of 1 minute). A previous study using this technology in the acute care setting, which also captured event contingent variables, found that nurses spent an average of 9.39 minutes at the bedside and patients were visited an average of 15.7 times per day (7.86 times per shift) for an average duration of 1.2 minutes (Sun et al., 2024). Compared to findings in the acute care setting, staff at the ALF visited residents an average of five times more often per day, despite the fact that ALF residents have a lower acuity level than those in the acute care setting. This increased number of visits could reflect the fact that memory care residents need help more often but at a lower intensity or skill level than those in an acute care setting. Thus, although CNAs require supervision and have a limited scope of practice, they can provide more time with residents, which could potentially reduce the number of falls. Further research could be conducted to ascertain whether a higher level of provider versus more time at the bedside ultimately improves resident outcomes.

The app allowed staff to resolve alerts 11.5 times per day. Further research is warranted to determine whether the 32.2 alerts per day, 20.7 in-person visits, and 11.5 resolutions per day in the mobile app represent a valuable use of staff's time and an increased benefit to residents compared to prior to installation. Unfortunately, without baseline data, the value added by staff surveillance is difficult to ascertain. Future studies could include subjective measures of staff burnout and patient satisfaction with the technology.

The technology allowed staff to observe shifts in resident activity and behavior based on staff interactions. Previously, understanding a resident's evolving needs relied heavily on reactive measures. Traditionally, interventions followed post-event analysis. For instance, if a resident frequently got up to use the rest room, a fall might prompt staff to investigate and discover a urinary tract infection (UTI) as

TABLE 1
Results of Continuous Monitoring of Assisted Living Facility Staff

Metric	Visits (*n*)	Notes
Staff visits to residents (total days = 170)	112,818	20.7 visits/day/resident
	Checks (*n*)	
Total number of times staff checked on a resident	175,178	32.2 times/resident/day
Resident checks using the app	62,360	11.46 times/resident/day
	Minutes	
Average visit duration	1.08	Per resident
Average response time to all alerts	8.57	
In person	6.4	
Via app	8.6	
Average response time to urgent alerts	3.0	
In person	3.3	
Via app	2.7	
Average duration of visit to resident's room (during alert response)	1.0	
	Alerts (*n*)	
Active device notifications to staff	20,928	3.84/patient/day
Leaving bed alerts	16,500	3.03/patient/day
Out of chair alerts	4,116	0.76/patient/day
Urgent alerts (resident on the floor)	127	0.06/patient/day
	Care Hours	
Total number of staff care hours in resident rooms	1,880.3	20.74 minutes/resident/room/day

Note. Staff were able to review an obfuscated video feed with pose estimation via the mobile app, which allowed them to respond via the app (with two-way audio) or in person, if needed.

the cause. However, with technology-enabled monitoring, staff can detect such patterns in real-time, allowing for proactive identification of issues, such as UTIs, before falls occur, thus enabling interventions and adjustments to prevent unintended negative outcomes. By quantifying changes, such as increased staff time in the room, nighttime ambulation frequency, or time spent in bed, remote surveillance may proactively inform care planning decisions. This ability to surveille patients for real-time adjustments to care could go beyond only responding to alerts; it could provide staff with a holistic picture of resident care, enabling them to identify and address potential issues before they escalate.

By understanding staff activities within an ALF, future studies can design clinical decision support to decrease redundant or unnecessary visits and cross-contamination between residents. Although we were unable to determine a fall reduction because of lack of preimplementation data, implementation of such technology provides data for analytic predictive modeling that could help reduce falls. Previous studies have demonstrated the capacity of such technology to assist in the reduction of falls (Sun et al., 2021). This technology could allow for the development of benchmarking data to accurately track and reduce falls in ALFs. To our knowledge, there have not been longitudinal studies with comprehensive data about staff and resident activities within ALFs. Providing this foundational knowledge will illuminate the timing of staff activities and the precise effects of those activities in a setting that is understudied.

LIMITATIONS

The current study is limited by lack of preexisting data by which to compare findings. There is also a dearth of concrete information on the amount of time spent with residents at the bedside in ALFs. This study may provide a foundation for future studies looking for comparison data.

The technology was installed for purposes other than research by the ALF. Therefore, the data collected were limited by the capability of the technology and desired variables of facility administrators and cannot answer all questions that the authors would like to answer. Future studies could include more information about residents and staff working at the facility to explore differences by resident and staff characteristics, as well as patient outcomes, such as falls.

CONCLUSION

The current study demonstrates the

potential of continuous monitoring technology to improve fall prevention in ALFs. By providing objective data on resident behavior and staff interactions, this approach offers valuable insights for proactive care planning and early detection of fall risk. Real-time information can inform targeted interventions before falls occur, ultimately promoting resident safety and well-being.

Our findings, alongside research in acute care settings (Sun et al., 2024), highlight the unique care dynamics within ALFs. Although staff in ALFs appear to spend more time with residents compared to acute care, further investigation is needed to determine the most effective balance between provider type and time at the bedside for fall prevention.

Analyzing staff activities can inform the development of clinical decision support systems that optimize efficiency and minimize cross-contamination risks. In addition, data collected by these technologies offer potential for developing predictive models to significantly reduce falls in ALFs, as well as collect objective data on falls that could establish fall prevention benchmarks specifically tailored to these facilities.

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