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Evaluation of Automated Video Monitoring to Decrease the Risk of Unattended Bed Exits in Small Rural Hospitals

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Objectives: This study aimed to evaluate the effectiveness of using 1 to 4 mobile or fixed automated video monitoring systems (AVMSs) to decrease the risk of unattended bed exits (UBEs) as antecedents to unassisted falls among patients at high risk for falls and fall-related injuries in 15 small rural hospitals.

Methods: We compared UBE rates and fall rates during baseline (5 months in which patient movement was recorded but nurses did not receive alerts) and intervention phases (2 months in which nurses received alerts). We determined lead time (seconds elapsed from the first alert because of patient movement until 3 seconds after an UBE) during baseline and positive predictive value and sensitivity during intervention.

Results: Age and fall risk were negatively associated with the baseline patient rate of UBEs/day. From baseline to intervention: in 9 hospitals primarily using mobile systems, UBEs/day decreased from 0.84 to 0.09 (89%); in 5 hospitals primarily using fixed systems, UBEs/day increased from 0.43 to 3.18 (649%) as patients at low risk for falls were observed safely exiting the bed; and among 13 hospitals with complete data, total falls/1000 admissions decreased from 8.83 to 5.53 (37%), and injurious falls/1000 admissions decreased from 2.52 to 0.55 (78%). The median lead time of the AVMS was 28.5 seconds, positive predictive value was nearly 60%, and sensitivity was 97.4%.

Conclusions: Use of relatively few AVMSs may allow nurses to adaptively manage UBEs as antecedents to unassisted falls and fall-related injuries in small rural hospitals. Additional research is needed in larger hospitals to better understand the effectiveness of AVMSs.

Key Words: falls, automated video monitoring, artificial intelligence, critical access hospitals, patient safety

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Approximately 2% to 4% of hospitalized patients fall annually,[1–4] and up to one-third of these falls result in injury.[5,6] Estimates of excess costs due to serious fall-related injuries vary from $7000[7] to $13,000[3,8] per injury. Costs associated with noninjurious falls include increased monitoring, length of stay,[3] and imaging to rule out injury.[9] For patients, noninjurious falls may increase fear of falling that limits mobility and accelerates functional decline.[10] Approximately 85% of falls are unassisted.[11] An unassisted fall is a "sudden, unintended, uncontrolled, downward displacement of a patient's body to the ground or other object,"[12] which is a system failure.[13,14] An assisted fall occurs when staff lower a patient to the ground. Assisted falls are significantly less likely to result in injury than unassisted falls[6,13] and are a system success in the context of early mobilization to prevent secondary functional decline.[15] Using gait belts to assist mobility is associated with decreased odds of unassisted falls and decreased odds that assisted falls result in injury.[6]

Since 2008, the Centers for Medicare & Medicaid Services have included serious fall-related injuries in its list of 14 preventable hospital-acquired conditions for which it no longer reimburses hospitals.[16] From 2014 to 2017, this pay-for-performance strategy resulted in a 13% reduction in all hospital-acquired conditions, but just a 5% reduction in serious fall-related injuries.[17] Two factors may account for this limited progress. First, falls are an outcome of the interaction between patient (e.g., age, muscle weakness, and impaired cognition),[1,6,18–20] environmental (e.g., unit/room design and clutter/tripping hazards),[1,21–23] and system risk factors (e.g., poor teamwork, the attitude that falls are inevitable, and gait belt usage).[6,24–26] Second, too few studies evaluate system interventions that improve nurses' ability to adaptively manage fall risk as a complex problem with a multifactorial etiology.[27,28]

Because of the prevalence of unassisted falls, many fall risk reduction interventions are intended to prevent unattended bed exits (UBEs) as antecedents to falls without restraining patients. Social interventions to prevent UBEs include hourly rounding and sitters. Hourly rounding has been associated with decreased risk of falls,[29,30] whereas use of sitters has had conflicting results.[31–34] Technical interventions to prevent UBEs include bed pressure-sensor alarms and central video monitoring (CVM). Randomized controlled trials of bed pressure-sensor alarms[35,36] revealed that their use did not significantly decrease fall rates[35,36] owing to the prevalence of false alarms.[36,37]

Hospitals began using CVM in 2012[38] as a lower cost alternative to sitters.[38–41] Central video monitoring uses unlicensed[38–41] or licensed personnel[42] to continuously observe up to 16 patients[38,40–42] on video monitors from a central location. To protect privacy, CVM uses live video and does not record.[39,40] Upon observing unsafe patient behavior, a monitoring technician may communicate directly with the patient via intercom, call the assigned nurse, activate the patient call system or an alarm, or use an overhead paging system.[40,41] Of 6 evaluations of CVM, 3 reported decreases in total fall rates of 20% to 29% and decreases in sitter-related costs,[38,40,43] 2 were underpowered because of too few patients[42] or cameras,[44] and 1 was descriptive without pre-post comparisons.[41] Limitations to CVM include:

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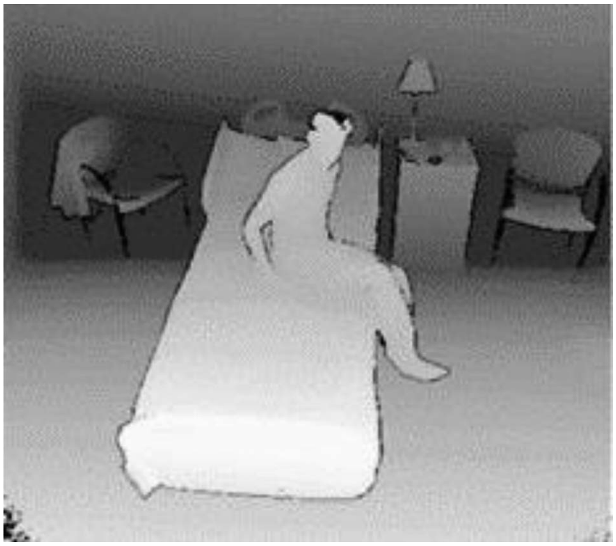


FIGURE 1. Simulated 3D grayed-out shapes produced by Ocuvera AVMS.

•cost of equipment and monitoring technicians,[38,40,44]
•potential for human error by monitoring technicians,[40]
•response delays due to hand-offs between monitoring technicians and nurses,[39,40] and
•privacy concerns of patients and staff.[42]

Automated video monitoring systems (AVMSs) use video streams to find the floor and bed and machine learning to detect body segments and then predict the likelihood that a patient will exit the bed.[45] At a threshold expectation of an UBE, the AVMS sends a predictive alert (i.e., before an UBE) and real-time video to nursing staff via a mobile device or central monitor.[45] The goal is to provide a nurse the time and information needed to assess a patient's behavior in clinical and environmental context (i.e., adaptively manage fall risk), respond to meet the patient's needs, and prevent an UBE.

An AVMS may mitigate limitations associated with CVM. First, an AVMS eliminates monitoring technicians, their associated costs, delayed response, and their potential for human error, misinterpretation of behavior, and miscommunication. Second, an AVMS may use 3-dimensional (3D) images that appear as grayed-out shapes (Fig. 1) rather than photographic images to mitigate privacy concerns. To our knowledge, the evidence needed to transfer AVM technology from pilot testing to standard of care does not exist. The purpose of this study was to evaluate the feasibility and effectiveness of using a prototypical AVMS from Ocuvera, LLC (Lincoln, Nebraska)[45] to decrease the risk of UBEs as antecedents to unassisted falls among patients at high risk for falls and fall-related injuries in small rural hospitals (SRHs). These hospitals may have higher fall rates than larger, urban hospitals[26,46] due to limited resources and a higher prevalence of older adults who are at high risk for falls and fall-related injuries.[26] This study was approved by the institutional review board of the University of Nebraska Medical Center.

METHODS

Setting, Design, Participants, and Procedures

From April 2017 to May 2018, we recruited 15 hospitals in a Midwestern state to participate in this no-cost study. We used a 1-group pretest-posttest design to compare patient and hospital rates of UBEs during baseline and intervention phases, which lasted approximately 5 and 2 months, respectively, within each hospital. To determine baseline rates of UBEs, the AVMS recorded patient movement during baseline but did not send predictive alerts to nurses. During intervention, nurses received alerts on mobile devices and a central monitor. Of the 15 hospitals, 13 were critical access hospitals licensed for 25 beds or less (Table 1). Patients admitted for acute care, skilled rehabilitation, observation, or hospice and deemed to be at high risk for falls or fall-related injuries were eligible to participate.

TABLE 1. Hospital Characteristics and Study Enrollment

Hospital	Bed Size	Camera No. and Type	Admissions During Baseline (n = 4680), n (%)	Admissions During Intervention (n = 3771), n (%)	Baseline Patients (n = 221), n (%)	Intervention Patients (n = 151), n (%)
A	100–200	4 fixed	1318 (28.2)	2440 (64.7)	21 (9.5)	15 (9.9)
B	≤25	1 mobile	171 (3.7)	126 (3.3)	8 (3.6)	8 (5.3)
C	≤25	1–2 mobile*	151 (3.2)	32 (0.8)	12 (5.4)	5 (3.3)
D	26–99	4 fixed	—	—	17 (7.7)	13 (8.6)
E	≤25	1–2 mobile*	185 (4.0)	45 (1.2)	3 (1.4)	7 (4.6)
F	≤25	1–2 mobile*	714 (15.3)	153 (4.1)	11 (5.0)	8 (5.3)
G	≤25	1–2 mobile*	472 (10.1)	86 (2.3)	13 (5.9)	5 (3.3)
H	≤25	1–2 mobile*	473 (10.1)	89 (2.4)	4 (1.8)	0 (0.0)
I	≤25	4 fixed	282 (6.0)	222 (5.9)	28 (12.7)	50 (33.1)
J	≤25	4 fixed	214 (4.6)	220 (5.8)	22 (10.0)	16 (10.6)
K	≤25	2 mobile	158 (3.4)	131 (3.5)	13 (5.9)	4 (2.6)
L	≤25	1 mobile	100 (2.1)	42 (1.1)	18 (8.1)	4 (2.6)
M	≤25	4 fixed	312 (6.7)	71 (1.9)	21 (9.5)	8 (5.3)
N	≤25	2 mobile	97 (2.1)	96 (2.5)	16 (7.2)	5 (3.3)
O	≤25	1 mobile	33 (0.7)	18 (0.5)	14 (6.3)	3 (2.0)

*These hospitals received 1 mobile camera during baseline and 2 mobile cameras during intervention.

Procedures included installing the AVMS, training nurses to consent patients and use the system, and collecting and analyzing patient demographic data, fall event data, and video data. We requested that hospitals report fall event data during the study using a secure online system developed for previous studies.[6,14] The AVMS consisted of a room sensor, mobile devices for nursing staff, and a central monitor at the nurse's station (Fig. 2). The room sensor included a Microsoft Kinect (Microsoft Corporation, Redmond, WA) for Xbox One depth camera (field of view, 70.6 degrees wide by 60 degrees tall), a touchscreen, and an internal computer to analyze patient movement and send predictive alerts when movement exceeded the threshold expectation of an UBE. The camera used an infrared signal for night vision and provided 3D images of grayed-out shapes (Fig. 1) by measuring the depth for each pixel as its distance to the camera's imaging plane.[45] Cameras were installed as mobile units on a cart or fixed units on a wall to accommodate the needs/environment of each hospital. Cameras were 3 to 6 ft from the foot of the bed and 6.5 to 7 ft above the floor. We provided onsite training for nurses with supporting documentation about the AVMS, starting/stopping patients, and consenting patients. We emphasized 2 topics:

•Point the camera at the foot of the bed to improve accuracy of predictive algorithms.
•Press the "Privacy Mode" button during sensitive patient care to stop the camera for 15-minute increments.

We regularly exchanged a hard drive within each room sensor, transported it to our office, downloaded system performance data and video to a restricted-access hard drive, and converted the video into numeric data for analysis. We manually identified UBEs in the video by viewing every sixth frame at high speed and then determining whether there was an associated alert for each identified UBE. To adjust for errors associated with this manual process, we randomly sampled for missed UBEs. To account for UBEs found by random sampling, we weighted the number of manually found UBEs using the ratio: (total time for given patient not within 7 minutes before and 2 minutes after a manually found UBE)/(total time not within 7 minutes before and 2 minutes after

FIGURE 2. Ocuvera AVMS.

a randomly found UBE). The average weight for a randomly found UBE was approximately 50.

Measures and Analyses

Measures included hospital characteristics (Table 1), patient demographics (Table 2), hospital admissions and fall event information, hours of video recorded, UBEs per patient, and lead time for baseline UBEs. We calculated 2 UBE rates:

•patient rate of UBEs per day = (total number of UBEs per patient/total hours of video per patient) × (24 hours per day) and
•hospital rate of UBEs per day = (total number of UBEs per hospital/total hours of video per hospital) × (24 hours per day).

To determine the potential prospective advantage of the AVMS, we measured the lead time for UBEs that occurred during baseline when nurses did not receive alerts. Lead time was the number of seconds that elapsed from the first alert generated by the system due to patient movement until 3 seconds after the UBE. If the system did not generate an alert until after the UBE, then lead time was negative. We calculated lead time if the patient movement that precipitated the alert began when the patient was lying in bed and was alone from the time movement began until 3 seconds after the UBE. We used descriptive statistics and hypothesis tests appropriate for the distribution and sample size of the measure to compare differences between baseline and intervention values. We attempted a mixed linear model to predict median lead time using patient as a random effect, but this model did not converge because of limited sample size. We report the specific tests used in the notes section of our tables and within figure titles. We considered *P* values less than 0.05 to be statistically significant and those less than 0.10 to be marginally significant (of interest) given our sample size of 15 hospitals and the value of identifying potentially promising evidence.[52,53] We used IBM SPSS Statistics version 25 to conduct all analyses (IBM, Armonk, New York).

We determined the positive predictive value (PPV) and sensitivity of alerts received by nurses during intervention. To determine PPV, 1 or 2 nurses from hospitals not participating in the study independently reviewed video of patient movement that led to alerts during intervention. Nurses classified an alert as "true positive" if they judged that patient behavior in the video warranted assessment or "false positive" if they believed that patient behavior did not warrant assessment. Disagreements were resolved by consensus when possible. To determine the sensitivity of the alerts, we calculated the proportion of UBEs during intervention that were preceded by an alert.

RESULTS

During the 13 months of the study, 408 patients consented to participate. We analyzed video from 372 (91%) patients (Table 1). Video was not analyzed when a camera was improperly positioned such that the bed was not fully visible for more than half of the admission, which typically occurred with mobile cameras during baseline. Five hospitals used fixed cameras, and 10 used mobile cameras. Approximately 4% of hospital admissions participated in the study.

Patient Demographics

The characteristics of patients did not vary significantly from baseline to intervention (Table 2). More than 90% of patients were

TABLE 2. Patient Demographics

Demographics	Aggregate	Baseline	Intervention	*P**
Age category	n = 358, n (%)	n = 216, n (%)	n = 142, n (%)	0.687
<65	29 (8.1)	17 (7.9)	12 (8.5)	
65–84	150 (41.9)	87 (40.3)	63 (44.4)	
85+	179 (50.0)	112 (51.9)	67 (47.2)	
Sex	n = 350, n (%)	n = 211, n (%)	n = 139, n (%)	0.826
Female	195 (55.7)	119 (56.4)	76 (54.7)	
Male	155 (44.3)	92 (43.6)	63 (45.3)	
Diagnoses†	n = 354, n (%)	n = 217, n (%)	n = 137, n (%)	0.549
Cardiovascular	47 (13.3)	32 (14.7)	15 (10.9)	
Fall history	24 (6.8)	14 (6.5)	10 (7.3)	
Gastrointestinal	19 (5.4)	12 (5.5)	7 (5.1)	
Infection	31 (8.8)	16 (7.4)	15 (10.9)	
Mental status change	22 (6.2)	9 (4.1)	13 (9.5)	
Neurological	23 (6.5)	13 (6.0)	10 (7.3)	
Orthopedic	47 (13.3)	29 (13.4)	18 (13.1)	
Renal\Urinary	22 (6.2)	16 (7.4)	6 (4.4)	
Respiratory	59 (16.7)	37 (17.1)	22 (16.1)	
Weak	19 (5.4)	14 (6.5)	5 (3.6)	
Other	41 (11.6)	25 (11.5)	16 (11.7)	
Fall risk category‡	n = 326, n (%)	n = 196, n (%)	n = 130, n (%)	0.459
Low	23 (7.1)	13 (6.6)	10 (7.7)	
High	116 (35.6)	75 (38.3)	41 (31.5)	
Very high	187 (57.4)	108 (55.1)	79 (60.8)	

*Differences between baseline and intervention phases calculated using the Pearson χ^2 test or Fisher exact test.
†Admitting diagnoses were sorted into categories consistent with those used by Morse et al.[47]
‡Fall risk scores from the assessment used by each hospital were categorized as low, high, or very high consistent with published studies.[48–51]

TABLE 3. Patient Rate of UBEs/Day During Baseline and Intervention by Patient Demographics

Category (n Baseline, n Intervention)	Patient Rate of UBEs/Day in Baseline, Median (Range)	P*	Patient Rate of UBEs/Day in Intervention, Median (Range)	P*
Sex		0.932		0.267
Female	0.00 (0.00–16.75)		0.00 (0.00–73.06)	
Male	0.00 (0.00–40.39)		0.00 (0.00–17.94)	
Age		<0.001		0.001
<65 y (17, 12)	0.78 (0.00–16.75)		2.14 (0.00–17.18)	
65–84 y (87, 63)	0.00 (0.00–40.39)		0.00 (0.00–73.06)	
85+ y (112, 67)	0.00 (0.00–4.26)		0.00 (0.00–13.42)	
Fall risk		0.015		0.130
Low (13, 10)	3.41 (0.00–15.75)		0.80 (0.00–73.06)	
High (75, 41)	0.00 (0.00–22.74)		0.00 (0.00–17.94)	
Very high (108, 79)	0.00 (0.00–40.39)		0.00 (0.00–17.18)	

*Nonparametric independent-samples median test.

65 years and older, and half were 85 years and older. Most were female; respiratory, cardiovascular, and orthopedic conditions were the most prevalent diagnoses. Approximately 93% of patients were at high or very high risk for falls.

Unattended Bed Exits

Of 221 patients in the baseline phase, 71 (32%) exited the bed unattended 507 times (mean, 7.14; median, 3.00; range, 1–66). Of 151 patients in the intervention phase, 47 (31%) exited the bed unattended 815 times (mean, 17.35; median, 6.00; range, 1–203). Weights were applied to the UBE count for 1 baseline patient (79-year-old man at high risk for falls whose UBE count increased from 22 to 66) and 1 intervention patient (79-year-old woman at low risk for falls, whose UBE count increased from 52 to 203). Age and fall risk were significantly associated with the rate of UBEs/day during baseline (Table 3). Specifically, patients younger than 65 years and those at low risk for falls had significantly greater median rates of UBEs/day than did older patients and those at high/very high risk for falls. Only age was significantly associated with the rate of UBEs/day during intervention; patients younger than 65 years had greater rates of UBEs/day than did older patients.

The hospital rate of UBEs/day ranged from 0 to 1.68 during baseline and from 0 to 5.16 during intervention (Table 4). Thus, it seemed that hospitals used the system for 2 different purposes during intervention: to intervene and prevent UBEs or to monitor patients as they exited the bed unattended. Specifically, the rate of

TABLE 4. Hospital Use of AVM System During Intervention and Comparison of Rate of UBEs Per Day by Study Phase

Hospital (Intervention Cameras)	Hospital Admissions* in Intervention, %	Patients at High/Very High Risk for Falls in Intervention, %	UBEs/Day: Baseline, n	UBEs/Day: Intervention, n	UBEs/Day: Difference	P†
Aggregate monitoring	3.11	89.0	0.43	3.18	2.75	0.043
A (4 fixed)	0.6	60.0	1.29	5.16	3.87	
D‡ (4 fixed)	—	91.7	0.15	0.18	0.03	
I (4 fixed)	22.5	97.3	0.40	3.60	3.20	
L (1 mobile)	9.5	100.0	0.03	1.14	1.11	
N (2 mobile)	5.2	100.0	0.12	0.24	0.12	
Aggregate intervening	6.59	96.5	0.84	0.09	−0.75	0.018
B (1 mobile)	6.3	100.0	0.49	0.00	−0.49	
C (2 mobile)	15.6	100.0	0.00	0.00	0.00	
E (2 mobile)	15.6	71.4	0.00	0.00	0.00	
F (2 mobile)	5.2	100.0	0.77	0.36	−0.41	
G (2 mobile)	5.8	100.0	1.44	0.20	−1.24	
H§ (2 mobile)	0.0	—	0.00	—	—	
J (4 fixed)	7.3	100.0	0.66	0.02	−0.64	
K (2 mobile)	3.1	—	0.98	0.04	−0.94	
M (2 mobile)	11.3	100.0	1.68	0.28	−1.40	
O (1 mobile)	16.7	100.0	0.62	0.00	−0.62	

*Fourteen hospitals reported admissions by month during the study for all patients admitted to acute, skilled rehabilitation, observation, or hospice beds.

†Differences between baseline and intervention phases calculated using the related-samples Wilcoxon signed ranks test.

‡Hospital D did not report admissions data.

§Hospital H did not contribute any patients to the intervention phase of the study.

UBEs/day increased from baseline to intervention in 5 hospitals, and it remained 0 or decreased from baseline to intervention in 9 hospitals. (One hospital did not participate in the intervention). Among the 5 monitoring hospitals, the aggregate rate of UBEs/day increased significantly from 0.43 during baseline to 3.18 (649%) during intervention; 3 of these 5 had fixed cameras. Nurses reported that when census was high, patients at low risk for falls were often admitted to rooms with fixed cameras and were not moved because of the cost of cleaning rooms. Conversely, among the 9 intervening hospitals, the aggregate rate of UBEs/day decreased significantly from 0.84 during baseline to 0.09 (89%) during intervention; 8 of these 9 had mobile cameras.

Among the 9 intervening hospitals during baseline, age was significantly and negatively associated with the rate of UBEs/day. Among 118 patients (Fig. 3A),

•71 (60%) had "0" UBEs/day and
•47 (40%) had a median rate of 1.31 UBEs/day (range, 0.04–22.74 UBEs/day).

Among these 9 during intervention, age was not significantly associated with the rate of UBEs/day. Among 61 patients (Fig. 3B),

•54 (89%) had "0" UBEs/day and

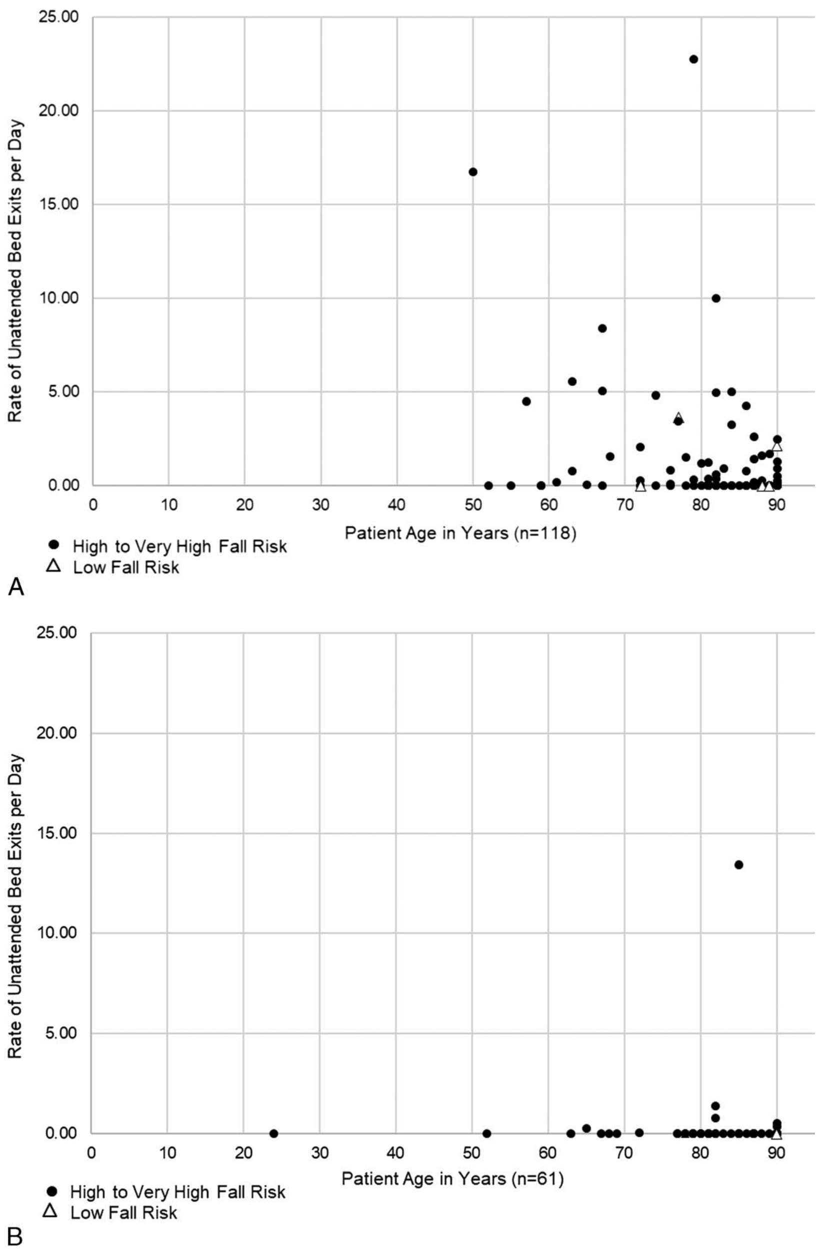
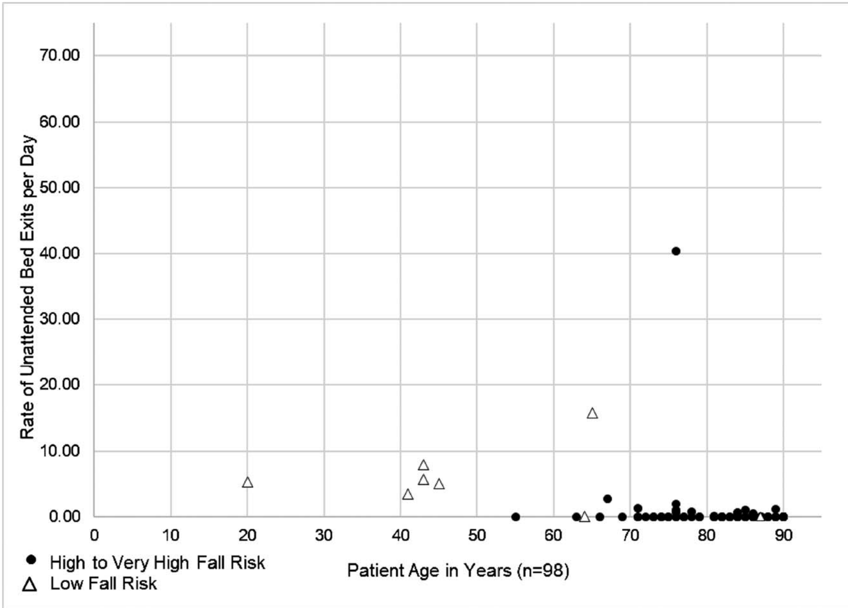


FIGURE 3. A, Baseline: age is significantly associated with rate of UBEs per day for 9 sites that used AVM system to intervene and prevent UBEs (Spearman $\rho = -0.333$, $P < 0.001$). B, Intervention: age is not associated with rate of UBEs per day for 9 sites that used AVM system to intervene and prevent UBEs (Spearman $\rho = -0.075$, $P = 0.567$).



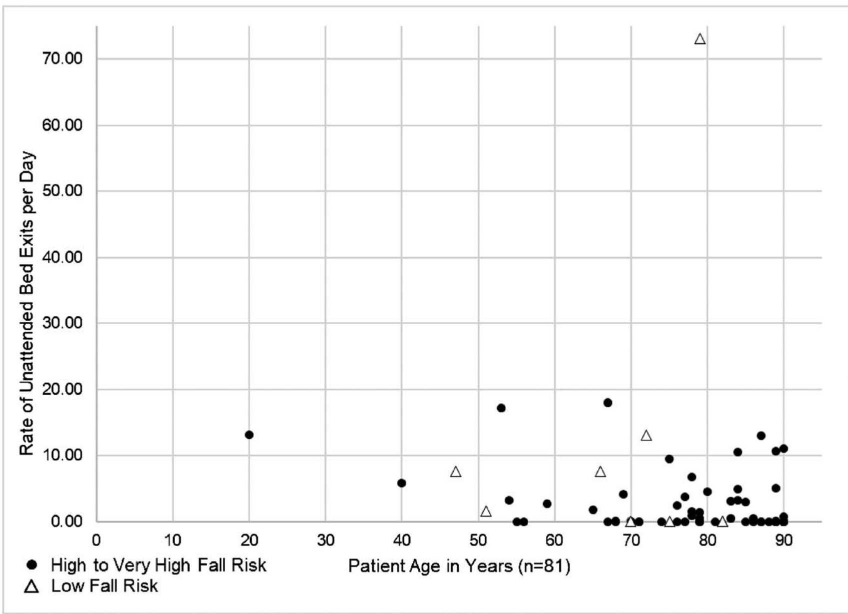


FIGURE 4. A, Baseline: age is significantly associated with rate of UBEs per day for 5 sites that used AVM system to monitor patients as they exited the bed unattended (Spearman $\rho = -0.412$, $P < 0.001$). B, Intervention stage: age is significantly associated with rate of UBEs per day for 5 sites that used AVM system to monitor patients as they exited the bed unattended (Spearman $\rho = -0.361$, $P = 0.001$).

•7 (11%) had a median rate of 0.54 UBEs/day (range, 0.054–13.42 UBEs/day).

Among the 5 monitoring hospitals during baseline, age was significantly and negatively associated with the rate of UBEs/day. Among 98 patients (Fig. 4A),

•77 (79%) had “0” UBEs/day and
•21 (21%) had a median rate of 1.11 UBEs/day (range, 0.07–40.39 UBEs/day).

Among these 5 during intervention, age was significantly and negatively associated with the rate of UBEs/day. Among 81 patients (Fig. 4B),

•44 (54%) had “0” UBEs/day and
•37 (46%) had a median rate of 3.72 UBEs/day (range, 0.06–73.06 UBEs/day).

Lead Time

We calculated the median lead time in seconds for the 318 UBEs associated with 64 of the 71 patients who exited the bed during baseline. The distribution of these medians was right-skewed (mean [SD], 53.61 [71.05]; median, 28.00; range, 0–396). To summarize these skewed data, we identified the 95% central range of the 64 medians[54] (mean [SD], 50.58 [56.99]; median, 28.50; range, 1–248). Among the latter 60 observations in the 95% central range, age

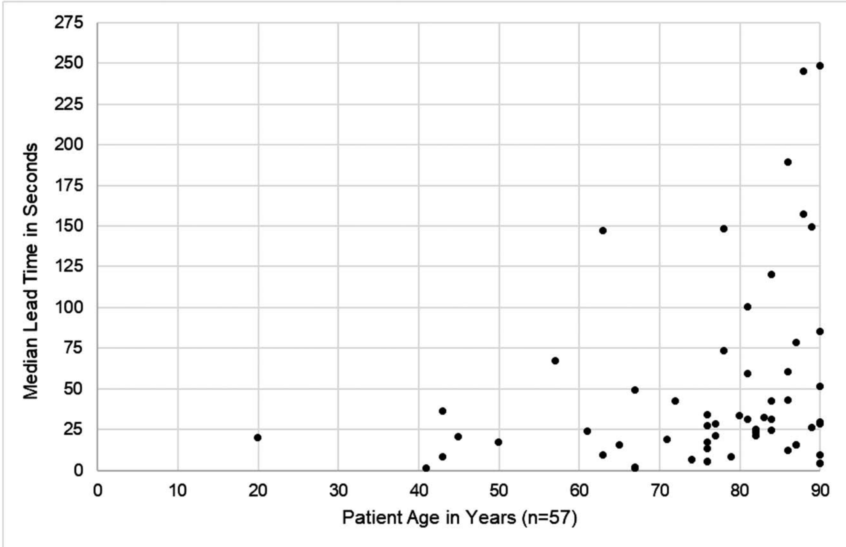


FIGURE 5. Baseline: age is significantly associated with median lead time (Spearman ρ = 0.359, $P = 0.006$).

was positively and significantly associated with median lead time (Fig. 5). Sex and fall-risk category were not significantly associated with median lead time.

PPV and Sensitivity

The denominator for calculating the PPV of the AVMS was the 4190 alerts associated with patient movement generated during intervention. Because 2 nurses reviewing alerts were not consistently available to independently review and concurrently resolve disagreements, we calculated a conservative and an optimistic estimate of PPV. The numerator for the conservative estimate was the 2362 alerts that 2 nurses agreed were true positives, or if there was only one review, it was also true positive. The numerator for the optimistic estimate was the 2487 alerts that 2 nurses agreed were true positives, and if there was a disagreement, at least one nurse identified the alert as true positive, or if there was only one review, it was also true positive. Thus, the conservative PPV was 56.4% and the optimistic PPV was 59.4%. Forty-seven patients exited the bed unattended 815 times during intervention. Of these 815 UBEs, 794 were preceded by an alert. Thus, the sensitivity of the AVMS to detect UBEs was 97.4%.

Fall Events

From baseline to intervention among the 13 hospitals with complete admissions and fall event data, total falls/1000 admissions decreased from 8.83 to 5.53 (37%), and injurious falls/1000 admissions decreased significantly from 2.52 to 0.55 (78%; Table 5). Approximately 41% of patient falls during the study occurred at bedside. From baseline to intervention among the 5 monitoring hospitals, no study patients fell at the bedside, and the proportions of:

•assisted falls increased significantly from 0% to 44%,
•injurious falls decreased marginally from 33% to 6%, and
•patients requiring increased postfall observation decreased marginally from 33% to 6%.

From baseline to intervention among the 9 intervening hospitals:

•the proportion of falls that occurred at the bedside decreased from 41% to 0%,
•total falls/1000 admissions decreased significantly from 13.37 to 3.67 (72.6%), and
•injurious falls/1000 admissions decreased marginally from 2.77 to 1.22 (56%).

Although not statistically significant, the proportions of patients requiring postfall observation and imaging decreased among all hospitals.

DISCUSSION

We sought to evaluate the feasibility and effectiveness of using a prototypical AVMS to decrease the risk of UBEs as antecedents to unassisted falls among patients at high risk for falls and fall-related injuries in SRHs. Our results demonstrate that the high sensitivity and median lead time of 28 seconds make it feasible to significantly decrease the median rate of UBEs/day in SRHs by 89% with 1 to 2 mobile cameras (Table 4, Fig. 3). Surprisingly, we found that the effectiveness of the AVMS to decrease rates of UBEs may be associated with camera type and hospital usage (Table 4, Fig. 4). Specifically, when census is high, hospitals using few fixed cameras may admit patients at low risk for falls to rooms with the AVMS and then use it to observe these patients as they exit the bed.

Regardless of camera type and hospital usage, when evaluated using the intention-to-treat principle,[55] the AVMS may have been effective in preventing bedside falls and decreasing total falls/1000 admissions by 37% and injurious falls by 78% (Table 5). In contrast, CVM decreased total fall rates by 20% to 29%.[38,40,43] Thus, nurses may use the sensitivity, lead time, and information generated by the AVMS to adaptively manage fall risk (e.g., apply and use a gait belt and assistive device) and decrease the risk of UBEs as antecedents to unassisted falls and fall-related injuries and not to limit safe mobility. This interpretation is consistent with a PPV value of nearly 60% and is in contrast to the alarm fatigue associated with bed pressure-sensor alarms.[36,37]

This may be the first study to report the incidence of UBEs among hospitalized patients and to report that age and fall risk are associated with a patient's rate of UBEs/day. Specifically, younger adults and those at low risk for falls may exit the bed unattended more frequently than older adults and those at high risk for falls (Table 3). However, the older a patient, the longer is the lead time provided by an alert so that older patients, who are at highest risk for fall-related injuries,[6,56] also have the greatest lead time before an UBE (Fig. 5). These findings are consistent with normative studies that have documented the negative correlation between age and physical function.[57–59]

TABLE 5. Fall Event Characteristics and Falls Per 1000 Admissions

		Hospital Used AVM to Monitor			Hospital Used AVM to Intervene		
Fall Event Characteristics	**All Falls During Study**	**Baseline**	**Intervention**	***P****	**Baseline**	**Intervention**	***P****
Fall location, n = 66, n (%)				0.729			0.271
Bedside	27 (40.9)	6 (40.0)	9 (50.0)†		12 (41.4)	0 (0.00)	
Not bedside	39 (59.1)	9 (60.0)	9 (50.0)		17 (58.6)	4 (100.0)	
Bathroom	24 (36.4)						
Chairside	13 (19.7)						
Hallway	1 (1.5)						
Room	1 (1.5)						
Fall assistance, n = 65, n (%)				0.004			1.00
Unassisted	47 (72.3)	14 (100.0)	10 (55.6)		20 (69.0)	3 (75.0)	
Assisted	18 (27.7)	0 (0.00)	8 (44.4)		9 (31.0)	1 (25.0)	
Extent of harm, n = 66, n (%)				0.070			0.241
No harm	52 (78.8)	10 (66.7)	17 (94.4)		23 (79.3)	2 (50.0)	
Harm	14 (21.2)	5 (33.3)	1 (5.6)		6 (20.7)	2 (50.0)	
Actions taken due to fall, n = 66, n (%)							
Increased observation	11 (16.7)	5 (33.3)	1 (5.6)	0.070	4 (13.8)	1 (25.0)	0.500
Imaging	9 (13.6)	3 (20.0)	2 (11.1)	0.639	4 (13.8)	0 (0.00)	1.00
Medication change	3 (4.5)	0	0	NA	3 (10.3)	0 (0.00)	1.00
Surgical procedure	1 (1.5)	0	0	NA	1 (3.4)	0 (0.00)	1.00

Falls/1000 Admissions‡	**Baseline**	**Intervention**	***P*§**			***P*§**			***P*§**
Total falls/1000 admissions	8.83	5.53	0.136	3.34	6.07	0.109	13.37	3.67	0.028
Unassisted falls/1000 admissions	6.56	3.04	0.214	3.34	3.21	0.593	9.22	2.44	0.173
Assisted falls/1000 admissions	2.27	2.49	0.285	0.00	2.86	0.109	4.15	1.22	0.028
Injurious falls/1000 admissions	2.52	0.55	0.025	2.23	0.36	0.109	2.77	1.22	0.080

*Differences between baseline and intervention phases calculated using the Fisher exact test.

†None of these bedside falls occurred among study patients.

‡Two hospitals either did not report admissions or did not report fall event data and were removed from this analysis.

§Differences between baseline and intervention phases calculated using the related-samples Wilcoxon signed ranks test.

Limitations and Future Research

Limitations to this study include missing data that decreased sample size, using admissions rather than patient days as the denominator to calculate fall rates, and using few cameras per hospital, some of which were fixed. Nurses failed to submit complete demographics for nearly 10% of patients, and we could not calculate fall rates for 2 of 15 hospitals because of missing admissions and fall event data. Using few cameras per hospital led to collecting admissions rather than patient days because we anticipated the need to explain the lack of an impact on fall rates of an intervention applied to 4% of admissions. Using few cameras may have led to "rationing" of the AVMS to patients at highest risk for falls, and using fixed cameras may have led nurses to use the AVMS for some patients at low risk for falls and to not use it for some at high risk for falls and fall-related injuries. As rare events, the rate of falls may vary considerably over a few months.[60] Thus, changes in falls/1000 admissions from baseline to intervention should be interpreted as indicating potential promising evidence rather than proof of causation. Finally, this study took place in SRHs in which half of patients were 85 years and older and should not be generalized to larger hospitals. Additional research is needed to better understand the effect of the AVMS on fall rates and the costs of post-fall assessment and treatment. These studies should be conducted in larger hospitals in which every patient at high risk for falls within a unit has access to an AVMS. These studies should compare fall rates and postfall costs between study and control units for up to 1 year before and after intervention.

CONCLUSIONS

Nurses used the high sensitivity and lead time provided by this prototypical AVMS to adaptively manage UBEs as antecedents to unassisted falls and fall-related injuries. Because of the low census in SRHs, just 1 to 2 mobile cameras may improve patient safety in these hospitals with limited resources and high proportions of older adults who are at high risk for falls and fall-related injuries. Additional research is needed to better understand the effect of an AVMS on fall rates and the costs of postfall assessment and treatment.

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