Automated Fall Detection Technology in Inpatient Geriatric Psychiatry: Nurses' Perceptions and Lessons Learned*

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RÉSUMÉ

Les personnes âgées hospitalisées présentent un haut risque de chute. Le système HELPER est un système de détection des chutes fixé au plafond qui envoie une alerte à un téléphone intelligent lorsqu'une chute est détectée. Cet article décrit la performance du système HELPER, qui a été testé dans un projet pilote mené dans un centre de santé mentale gériatrique. La précision du système pour la détection des chutes a été comparée aux données de l'hôpital liées à la documentation des chutes. Au terme du projet pilote, le personnel infirmier a été interviewé afin de documenter comment cette technologie était perçue. Dans cette étude, le système HELPER n'a pas permis de détecter une chute qui a été documentée par le personnel, mais en a détecté 4 autres qui n'avaient pas été documentées. Bien que la sensibilité du système soit élevée (0.80), les fausses alarmes qu'il génère diminuent sa valeur prédictive (0.01). Les entrevues avec le personnel infirmier ont permis de recueillir plusieurs informations utiles liées au fonctionnement de cette technologie dans un environnement réel; ces données seront utiles aux ingénieurs travaillant sur de tels systèmes et sur des technologies associées aux soins de santé et aux services sociaux.

ABSTRACT

Hospitalized older adults are at high risk of falling. The HELPER system is a ceiling-mounted fall detection system that sends an alert to a smartphone when a fall is detected. This article describes the performance of the HELPER system, which was pilot tested in a geriatric mental health hospital. The system's accuracy in detecting falls was measured against the hospital records documenting falls. Following the pilot test, nurses were interviewed regarding their perceptions of this technology. In this study, the HELPER system missed one documented fall but detected four falls that were not documented. Although sensitivity (.80) of the system was high, numerous false alarms brought down positive predictive value (.01). Interviews with nurses provided valuable insights based on the operation of the technology in a real environment; these and other lessons learned will be particularly valuable to engineers developing this and other health and social care technologies.

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Worldwide, falls are a leading cause of death by accident, second only to traffic accidents (World Health Organization, 2007). The costs associated with managing falls-related injury are placing a substantial financial burden on health care systems worldwide (World Health Organization, 2007; Tiedemann, Murray, Munro, & Lord, 2008). In Canada, the annual cost of falls among seniors was estimated in 2004 to be $2 billion (SMARTRISK, 2009). In 2006, in the United States, the total cost of falls was estimated at $19 billion (Stevens, Corso, Finkelstein, & Miller, 2006), with estimates increasing to $34 billion in 2013 (Centres for Disease Control and Prevention, 2015).

Falls in older adults are associated with a number of factors, including increasing age (Stalenhoef, Diederiks, Knottnerus, Kester, & Crebolder, 2002) and associated functional and cognitive impairment, multiple co-morbidities, delirium and confusion (Kallin, Jensen, Olsson, Nyberg, & Gustafson, 2004; Vassallo, Vignaraja, Sharma, Briggs, & Allen, 2004), number and types of medications such as high-dose antipsychotics and psychotropics (Blair & Gruman, 2005; Tinetti, 2003; Edelberg, 2001), poverty, hazardous living situations (Public Health Agency of Canada, 2005), and inadequate footwear (Menant, Steele, Menz, Munro, & Lord, 2008).

In hospital, the incidence of falling is greatest among patients 65 years of age and older (Abreu, Mendes, Monteiro, & Santos, 2012; Brand & Sundararajan, 2010). Falls occur most frequently in patient bedrooms and bathrooms (Abreu et al., 2012; Blair & Gruman, 2005), during the night (Hitcho et al., 2004; Tängman, Eriksson, Gustafson, & Lundin-Olsson, 2010), and more frequently in psychiatric units than in acute wards (Tideiksaar, Feiner, & Maby, 1993). The incidence of falling among institutionalized older adults is high, estimated at greater than 40 per cent (Rubenstein & Josephson, 2002). Fall rates among hospitalized older adults have ranged from 3.56 per 1,000 patient days (Bouldin et al., 2013) to 8.0 per 1,000 patient days (Enloe et al., 2005), with injurious fall rates ranging from 10 per cent (Hitcho et al., 2004) to 26 per cent (Bouldin et al., 2013). Falls occurring in hospitals extend length of stays and increase health care costs (Bates, Pruess, Souney, & Platt, 1995).

Background

Fall Prevention

There is much interest in the use of technology to prevent falls from occurring, specifically technologies aimed at alerting care providers to situations in which there is an increased risk of falls. Currently, a number of technologies are used in hospital and long-term care home settings for fall prevention, including bed alarms and movement detecting sensors (Bonner, 2006). Bed alarms are commonly used in hospital settings as an easy and efficient way to monitor the movements of patients at risk for falling and are often one component of multifaceted fall prevention programs (Hubbartt, Davis, & Kautz, 2011). The bed alarms consist of pressure-sensitive mats that trigger an alarm when patients get out of bed (Diduszyn, Hofmann, Naglak, & Smith, 2008; Tideiksaar et al., 1993). Studies on bed alarms have found contradictory evidence of their efficacy in preventing falls, with non-randomized methodologies finding fall rate reductions of 18 per cent to 54 per cent (Morton, 1989; Diduszyn et al., 2008) whereas randomized controlled trials have found no reduction in fall rate (Tideiksaar et al., 1993; Kwok, Mok, Chien, & Tam, 2006). Another study, aimed at increasing the use of bed alarms in a hospital setting, also found no reduction in falls (Shorr et al., 2012). Movement-detecting sensors include those in which devices are either incorporated into clothing or attached to clothing that provide an alert when the patient bears weight or assumes a vertical position. Studies examining the efficacy of these types of sensors have also been conflicting, with some noting a reduction in falls (Kelly, Phillips, Cain, Polissar, & Kelly, 2002) and others finding no reduction in falls (Cumming et al., 2008). Although many wearable sensors are unobtrusive, they have been deemed inappropriate for confused patients who tend to remove them (Widder, 1985).

Fall Detection

In addition to the use of technology to alert for the potential of falls (fall prevention), there are benefits associated with the use of technology to alert for the occurrence of falls (fall detection). There is evidence that the likelihood of recovery from a fall is dramatically reduced the longer a person remains without help (Institute of Medicine (US) Division of Health

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Promotion and Disease Prevention, 1992). In an effort to decrease the response time to assistance, automatic fall detection has been an active and rapidly growing research area over the past decade. Even so, the field is young in the sense that many different approaches are still being pursued, and the vast majority of the research is still taking place in laboratory settings. As such, these technologies have not yet shown evidence of impacting response time to assistance or health outcomes, although they have begun to provide an effective methodology for studying the causes and antecedents of falls (Gietzelt et al., 2012; Kangas, Korpelainen, Vikman, Nyberg, & Jamsa, 2015).

Fall detection technologies fall into two main categories, wearable devices and ambient sensors embedded in the environment. Wearable fall detection devices use accelerometers and gyroscopes to detect sudden fast movements, impacts, and body orientation (Igual, Medrano, & Plaza, 2013; Gietzelt et al., 2012; Kangas et al., 2015). Recent developments in this area include a new focus on smartphones as the wearable device (Habib et al., 2014). To be useful, these devices must be worn continuously and often must be secured tightly against the body, which can cause skin integrity problems in older adults and can be especially cumbersome at night.

A variety of ambient sensors have been studied, including floor vibration sensors (Tzeng, Chen, & Chen, 2010), acoustic sensors (Li, Ho, & Popescu, 2012), and video systems. To be effective, floor sensors must be tuned to the particular deployment environment and can be fooled by heavy furniture, whereas acoustic sensors must contend with competing background sounds such as televisions that may be set at high volumes by older adults. Most video-based fall detection research has focused on single-camera solutions (Igual et al., 2013; Mirmahboub, Samavi, Karimi, & Shirani, 2013; Feng, Liu, & Zhu, 2014), but falls that are fully or partially occluded from the camera present a significant challenge to these systems. Some researchers have deployed multi-camera systems to deal with this challenge, either calibrating and synchronizing the cameras to work together as a coordinated unit (Cucchiara, Prati, & Vezzani, 2007) or using the cameras as independent fall detectors and combining the results into a single output (Rougier, Meunier, St-Arnaud, & Rousseau, 2011).

A simpler approach to the challenge of occlusions is to use a ceiling-mounted (rather than a wall-mounted) camera; however, given the nature of the physical environment and clinical population with which the technology will be used, this may not always be feasible. For example, ceiling-mounted installation is challenging in older facilities where access to power sources and network connectivity are not readily available, or with patient populations who may become suspicious or agitated by visible devices. When taking this approach, a sufficiently wide-angle lens must be used to ensure that the camera's field of view – the region it can see – will cover the room being monitored. Another challenge faced by traditional ambient-illumination cameras is that they are heavily dependent on the lighting of the sensed environment. They are challenged by lighting fluctuations and work poorly or not at all in dark rooms. Active near-infrared (IR) illumination provides a solution, allowing the cameras to work in darkened rooms without disturbing the inhabitants.

A recent trend in near-IR illuminated fall detection is the use of depth images produced by the Microsoft Kinect sensor (Planinc & Kampel, 2013; Mastorakis & Makris, 2014; Rantz et al., 2014; Zhang, Conly, & Athitsos, 2014; Stone & Skubic, 2015, Skubic et al., 2016). A drawback of this sensor is its limited field of view (defined by 70- and 60-degree angles, horizontally and vertically, for the Kinect v2), which makes it impractical to use in a ceiling-mounted location (Kepski & Kwolek, 2014). Wide-angle lenses exist for the Kinect, but they result in substantially lower-quality depth images. Studies using the Kinect frequently place it on the wall near the ceiling to improve its field of view and reduce occlusions, but both problems persist. It has been suggested that using multiple Kinect sensors may be necessary to make further improvements in these areas (Stone & Skubic, 2015), but interference between the multiple near-IR light sources may present a challenge for this approach. One research team has mounted the Kinect on a robot that patrols its environment searching for fallen people (Volkhardt, Schneemann, & Gross, 2013), but this approach may not be tolerated well by older adults, particularly those experiencing dementia, paranoia, or delusions.

Fall Detection Research Environments

To date, the vast majority of fall detection studies test on data sets created by healthy young adults performing a limited set of scripted falls and non-fall activities in a laboratory setting (Igual et al., 2013). There are very few reports of evaluations done under authentic real-world conditions, such as hospitals (Rantz et al., 2014), elder-care facilities (Kangas et al., 2015; Debard et al., 2016), or the homes of older adults (Gietzelt et al., 2012; Stone & Skubic, 2015; Skubic et al., 2016; Debard et al., 2016), where system deployment is continuous and the inhabitants go about their normal daily activities. There are numerous reasons why studies conducted in natural environments are more difficult. For starters, laboratory-based studies typically have no problem

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recruiting participants since the research personnel themselves can participate, and the number of simulated falls is limited only by time and budget. However, the similarity of these samples to the corresponding motions of older adults may be poor and thus may not generalize well to the intended purpose (Debard et al., 2016). In contrast, in a natural environment, eligible participants may not consent or may withdraw for many reasons, and naturally occurring falls happen infrequently. This can result in a very low incidence of falls, with a resulting loss of statistical generalizability. As a compromise, some studies use a hybrid model, utilizing both simulated and naturally occurring falls within the same deployment environment (Stone & Skubic, 2015; Skubic et al., 2016).

In addition, laboratory-based studies typically test new devices or algorithms for the first time, so it is appropriate to test in convenient locations and common to test under a limited range of conditions. For example, these studies are typically conducted in well-lit rooms, and if a study does not specifically target the problem of occlusions, it will likely take place in an area cleared of furniture and other obstacles. In contrast, a fall detection system intended for real-world deployment is expected to perform well under a variety of lighting conditions, including changing light, moving shadows, and darkened rooms. Similarly, in a laboratory study it is not expected that the camera will cover the entire room, so the potentiality of a fall occurring outside the coverage area is not considered or included in the performance results.

Complex solutions such as multiple synchronized cameras are worthy of exploration in a laboratory but may not be tested in a natural setting because they prove too costly or complicated for widespread deployment. At least as important is the fact that the falls and non-fall activities employed in laboratory settings are scripted in advance. Although these simulations are carefully designed to include several different fall types and confounding non-fall activities (e.g., transfers, sitting quickly), they cannot express the full heterogeneity of individual behaviour and range of activities that are found in natural settings. This can lead researchers to develop algorithms that perform well on their test cases, but less well in natural settings. Moreover, during laboratory testing a fall detection system will operate only while the simulated falls and non-falls are being conducted. In contrast, fall detection systems in natural settings are expected to run continuously for many hours at a time. This vastly increased operation time results in more opportunities for false alarms to occur.

For all these reasons, it is worth noting that both true positive rates and false alarm rates are measuring something quite different for laboratory studies than for studies conducted in natural environments. Table 1 presents performance data from a representative set of studies that used video data to detect falls in laboratory settings. Table 2 presents results from fall detection studies that took place in natural environments. Since there are a limited number of such studies, Table 2 includes both ambient and wearable approaches, as well as studies employing stunt actors or capturing naturally occurring older adult falls. When sufficient data is given, PPV is reported even if it was not in the original study. These findings are consistent with previous observations (Gietzelt et al., 2012; Kangas et al., 2015; Debard et al., 2016) that fall detectors are likely to perform significantly less well under real-world conditions than in the laboratory.

HELPER System

This article describes a pilot test of a real-time fall detection system, utilizing 2D imaging and active near-IR technology, that was conducted in a geriatric psychiatry unit in a tertiary care centre. This system comprises a set of independent fall detection devices, each of which can send alerts that a fall has occurred to a set of smartphones over a private network. Dubbed the HELPER (Health Evaluation Logging and Personal Emergency Response) system, this system builds on work presented in other studies (Lee & Mihailidis, 2005; Belshaw, Taati, Giesbrecht, & Mihailidis, 2011; Belshaw, Taati, Snoek, & Mihailidis, 2011). Within this system, each fall detection device is responsible for monitoring a single room, and the device is installed in the centre of that room's ceiling. Each device is equipped with a single 2D camera, a wide-angle lens, a near-IR light array, and a Linux-based processor. The wide-angle lens allows the camera to view the entire room, while the near-IR light array allows the system to operate equally well during daytime and nighttime hours. The device takes a continuous stream of images and processes them in real time, using computer vision and machine-learning algorithms, to detect falls that may occur within the room. Since a person lying in bed looks substantially similar to a person lying on the floor from an overhead perspective, a "safe zone" is established in each room to indicate the location of the bed. This allows the system to quickly filter out events generated by the motion of a person lying in bed. The vast majority of images taken by the system are discarded without any person ever viewing them. However, when a potential fall is detected, the system saves a sequence of images to disk, recording approximately five minutes immediately preceding the fall. This provides an opportunity for the research team to understand what events trigger (true and false) fall detections.

The institutional version of the HELPER system is designed to be installed on a secure private network that is shared with a set of smartphones carried by nurses

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Table 1: Performance results for studies using video data to detect falls in the laboratory

Citation / Approach	Sample Characteristics	Results	
Belshaw et al., 2011 Ceiling-mounted RGB camera, wide-angle lens	Laboratory (actors: grad students) 195 fall events. Each contains 7 minutes of non-fall video before the fall. All frames are classified independently.	Sensitivity: .92 Specificity: .95 PPV: not given	
Rougier et al., 2011 Majority vote between multiple independent RGB cameras, to handle occlusions.	Laboratory (actor: one elder-care clinician) 75 events, for a total of 12 minutes	Results are given in terms of ROC curve. Best result: Sensitivity: .98 Specificity: .98 PPV: not given	
Mirmahboub et al., 2013 Single RGB camera (wall mounted)	Laboratory (one unspecified actor) 736 actions	Sensitivity: 1.0 Specificity: .93 PPV: .58	
Planinc & Kampel, 2013 Kinect (SDK skeleton tracking)	Laboratory (2 young adult actors) 72 events (40 falls, 32 non-falls)	Approach 1: Sens: .78 Spec: .97 PPV: .97	Approach 2: Sens: .93 Spec: .86 PPV: .88
Kepski & Kwolek, 2014 Accelerometer to detect fall; ceiling-mounted Kinect (depth images) to confirm lying position	Laboratory (30 young volunteers total; 5 in lying-pose detection experiment) Narrow field of view (approx. 11' x 12' after Nyco zoom)	For lying-pose detection: Sensitivity: "slightly smaller than 100%" Specificity, PPV: not given	
Feng, Liu & Zhu, 2014 Single RGB camera. Data from 2 publicly available data sets: Rougier et al. (2011); Chua, Chang, & Lim, (2015)	Rougier data set (described above): Feng's study used a selected subset of this data, from the camera with the least distortion. Chua data set (described below): Feng's study used this full data set.	Rougier data: Sensitivity: .98 Specificity: .97 PPV: not given Chua data: Sensitivity: .95 Specificity: 1.0 PPV: not given	
Chua el al., 2015 Single IP surveillance camera (RGB), wall mounted	Laboratory (unspecified number of young adults) 30 non-falls, 21 falls	Sensitivity: .90 Specificity: .94 PPV: .90	

Note. **IP = Internet protocol (standard surveillance camera); PPV = positive predictive value; RGB = red/green/blue (standard colour camera); SDK = software development kit (Microsoft-provided skeleton tracking algorithm for Kinect); ROC = receiver operating characteristic.**

on the unit. The phones run a mobile app designed to receive alert messages from the system. When a potential fall is detected, an alert message indicating the room number is sent to each of the phones on the unit. After a fall detection event occurs, the HELPER system sleeps for five minutes to avoid sending a continuous stream of fall alerts while the person who fell remains on the floor. After this five-minute "sleep" period, the system resumes its normal operation of monitoring for falls.

The HELPER system was pilot tested in a real-world study in two geriatric psychiatry units in a regional mental health care facility. The purpose of this study was threefold: (1) to explore nursing staff perceptions of this fall detection technology and its value to clinical practice, (2) to report on lessons learned about conducting technology evaluations in authentic environments, and (3) to describe the performance of the HELPER system in detecting falls in order to identify still-needed technological improvements. Consistent with user-centred design principles, which promote end-user involvement in the ongoing design, development, and evaluation of new technologies (Gulliksen et al., 2003; Lu et al., 2011), the input of nurses in this study was valued as an opportunity to ensure that the needs of HELPER system end users are included in the iterative design process and to inform quality improvement.

Methods

Setting and Participants

This study was conducted in two geriatric psychiatry units within a regional mental health hospital in Ontario. Combined, these specialized secured units consist of 55 beds. One of the units focuses on the management of psychological and behavioural symptoms associated with cognitive impairment (25 beds), while the other

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Table 2: Performance results for studies detecting falls in natural environments

Citation / Approach	Sample Characteristics	Results
Kangas et al., 2015 Accelerometer attached to belt	16 elder-care facility units Study lasted 10 months; individual participants involved from 5 to 155 days. 15,500 hours data (1.8 years)	Sensitivity: when wearing device (12 of 15 falls): .80 overall (3 falls when device not worn): .67 748 false alarms (1 per 20.4 usage hours) PPV: .02
Gietzelt et al., 2012 Accelerometer and RGB camera. Results combined with Kalman filter.	3 homes of older adults (who wore the accelerometer 10 hours/day) Study length: 60 days, participants' involvement ranged from 28–43 days.	Sensitivity: when wearing device (2 out of 5 falls): .40 overall (3 falls when device not worn): .25 (2 detections by accelerometer; 0 by camera) False alarms averaged 1.3 to 2.4 per day, for different participants PPV: not given
Rantz et al., 2014 Kinect (depth images), wall-mounted	Six private hospital rooms; 8 months' data collection 50 falls simulated by stunt actors. One patient fall occurred but was not captured due to a power outage.	Stunt actor falls: Sensitivity: .92 Specificity: .95 Average of 11 false alarms/month per room PPV: not given
Stone & Skubic, 2015 Kinect (depth images). Offline processing following data collection.	13 apartments of older adults; one year of data collection 9 naturally occurring falls, 445 falls simulated by stunt actors. Results from these are combined.	Sensitivity (computed separately by fall type): 71–98% (near to camera) 5–79% (far from camera) 0–55% (occluded) Results are given at a 1-per-month false alarm rate on the associated ROC curve. PPV: not given
Debard et al., 2016 Standard IP surveillance cameras: RGB by day, IR at night	4–7 residences (nursing home, assisted living, and community dwelling): 3 to 20 months data collection 34 naturally occurring falls (29 occurred on camera, 21 considered in the analysis)	Sensitivity: (for the 21 falls analysed): .62 (for all falls): not given Average of 178.7 false alarms per day PPV: (in the 24-hour period before each analysed fall): .0035 (for the full video recordings): not given

Note. **PPV = positive predictive value; RBG = red/green/blue (standard colour camera); ROC = receiver operating characteristic.**

unit manages a variety of psychiatric illnesses including affective disorders, personality disorders, and schizophrenia (30 beds). Patients on these units tend to range from 60 to 90 years of age and all have persistent and severe mental illness requiring longer-term psychiatric tertiary care. The average length of stay in these units is 120 days, with an occupancy rate of 90 per cent. The nurse-to-patient ratio during day and evening shifts is 1:5 and 1:10 during the night shift, although supplemental staffing occurs according to acuity and occupancy census. This geriatric psychiatry program focuses on assessment, treatment, rehabilitation, prevention, family/community support, and education provided by a multidisciplinary team in addressing the physical, mental, spiritual, cultural, psychological, and social aspects of aging. Some patients may require constant observation when they are considered a danger to themselves or others. All patients are screened for the risk of falling upon admission, and a fall protocol is then implemented depending on level of risk. Fall prevention protocols can include a variety of strategies including more frequent observations, regular toileting routine, bed alarms, bedside egg crate mattresses, hi/low beds, and appropriate footwear recommendations. Throughout the night, nursing staff on these units complete regular rounds on a 30-minute basis, investigate sounds or unusual noises, and respond to bed alarms, which are used for patients at high risk of falls; these practices were continued as usual during the study time period.

Patients, and/or their substitute decision-makers, admitted to rooms in which the HELPER device was installed were invited to participate in this study and provided signed consent. Although there were no specific patient-related eligibility criteria, it was specified that patients would be excluded if their physician indicated that participation would be detrimental to their care or if the patient required special observation rooms, as the HELPER units were not installed in these rooms. (Neither of these conditions occurred during the study.)

All night-shift nursing staff were invited to participate in the study; their participation in the study included the expectation that they would be trained on the use of the HELPER system and smartphone, carry the

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HELPER system smartphone when on shift, and, at the end of the study time period, participate in an individual interview to assess their perceptions of this technology. To participate in an interview, nurses had to have utilized the HELPER system in the care of patients, defined as carrying the smartphone to which alerts were transmitted. Minimum experience with this technology was not specified as a prerequisite to participate in the interviews.

Measures and Analysis

Chart Audit

The charts of all patients admitted to rooms in which the HELPER devices were installed were reviewed to abstract data on patient age, gender, marital status, number of medications prescribed and types, number of medications prescribed as needed (PRN medications) and type, diagnosis, and results of the Falls Risk Assessment Tool (FRAT) administered at the time of admission to the geriatric psychiatry program. The FRAT consists of the Morse Fall Scale (Morse, Black, Oberle, & Donahue, 1989), the Braden Scale for Predicting Pressure Sore Risk (Bergstrom, Braden, Laguzza, & Holman, 1987), and a footwear screen. These scales are used to determine patient risk for falling and contributed to decisions made about patient placement in rooms closest to the nurses' station so that high-risk fallers could be closely monitored. Chart audit data was analysed using SPSS (IBM Corp.; released 2015. IBM SPSS Statistics for Windows, Version 24.0.) to generate descriptive statistics.

Fall Occurrences

Information on falls during the study time period was gathered from hospital records on fall occurrences, as recorded in the Patient Safety and Reporting System (PSRS). This form is completed whenever a patient falls. It includes information on the date and time of the fall, resulting level of harm (1 = no injury/harm assessment required; 2 = no injury/harm intervention monitoring required; 3 = minor to moderate injury/harm; 4 = serious injury/harm/disability; 5 = death), and a narrative description of the event.

Interviews with Nurses

Interview questions were framed to capture nurses' perceptions of the technology and its value to clinical practice, including optimal features and desired information from the technology. Three overarching objectives framed the interview guide: (1) to determine views and opinions on how the HELPER worked (e.g., Did the HELPER system help you to complete your care tasks more efficiently? Did the HELPER alert you to situations that normally you would have otherwise not known about? Did you find HELPER's alerts to be helpful? Why or why not?); (2) to determine design criteria for the device (e.g., In general, what features or functions for a fall device are important for your work as a nurse?), and (3) to determine data that the system needs to generate and how clinicians will interact with system (e.g., What sort of data is important for the system to collect? What kind of data is important for you to receive?). Interview participants were also asked to comment on their use of technology in their daily practice and routines and the amount of experience they had working with the HELPER system. The interview guide was given to participants prior to the interview for review.

Interviews were conducted over two days at the end of the study time period. Nurses who participated in the study and who were working on the days that the interviews were conducted were invited to participate. There were opportunities for staff working either day or night shifts on the interview days to participate in the interviews. On both of these days, extra nursing staff were scheduled so that positions could be back-filled while nurses left the units to complete the interviews. The interviews were conducted by a trained research associate who was not actively involved in the implementation of the technology in this setting and who did not know the participants. A member of the research team who worked on the development and implementation of the technology attended these interviews as an opportunity to clarify or further explore technological issues that could potentially arise in the interviews that may have been beyond the scope of the interviewer. Interviews were conducted to the point of saturation, that is, no new ideas or themes were generated in the final interviews that were completed (Strauss & Corbin, 1998). All of the interviews were digitally recorded and transcribed.

Interview transcripts were analysed using a qualitative naturalistic inquiry approach (Lincoln & Guba, 1985). Two authors (LMH, KM) independently reviewed the interview transcripts to generate broad categories and identify emerging themes consistent with prescribed practices for thematic analysis (Braun & Clarke, 2006). Greater clarity in the emerging themes was achieved following discussions and further review of the transcripts. This inter-rater coding served to prevent selection bias regarding affirmative quotes, taking into account the presence of negative case statements. Notes taken during the coding process were compared to ensure that the observations of the data reflected emerging themes. Resulting themes and illustrative quotes were shared with the interviewer (RC) and the research team member (MC) who was present during the interviews to further validate the identified themes.

HELPER System Performance

The HELPER system was configured to monitor patient rooms daily from 7:00 p.m. to 7:00 a.m. This time period was selected because patients on these units typically spend their days in a common room under direct supervision and their nights in private rooms. Some face a significant risk of falling at night since they may rise to visit the bathroom or to pace, even though they may not be fully ambulatory. The system was installed in five rooms (three in one unit, and two in the other) for 12 weeks each. The rooms were all in close proximity to the nurses' station since patients at higher risk of falling are typically admitted to these rooms.

Each time the system detected a potential fall, a series of images leading up to the fall was stored to disk for further analysis. At the end of the study, the fall detection devices were removed from the hospital, and the data were transferred to secure storage for analysis. All of the image sequences from events detected by the HELPER system were reviewed and categorized as actual falls, false alarms, and boundary cases by visual inspection. A boundary case was defined as a situation where a patient might have fallen, either shortly before or shortly after the system raised an alarm, but the images recorded by the system for the raised alarm do not depict a fall in progress. Image sequences that show a person falling, whether onto furniture or the floor, were categorized as actual falls, and sequences with no evidence of a fall were categorized as false alarms.

This study was approved by the Research Ethics Board, Western University (London, Ontario), and the University Health Network Research Ethics Board (Toronto, Ontario).

Results

A total of six consented patients were admitted to rooms with HELPER devices during the study time period. Patient characteristics are presented in Table 3. Half of the patients were over 70 years of age and the majority were male; all six were diagnosed with dementia. On average, patients were taking 2.8 medications. All six patients were prescribed antipsychotics. On average, these patients were prescribed 1.5 additional medications to be taken as needed. Four patients had admission FRAT scores; all four were classified as having a high falls risk on the basis of the Morse Fall Scale; three had footwear that put them at high risk for falls. Half of the patients with FRAT scores had Braden scores that placed them at high risk for falls.

Table 3: Study participant profile (*n* = 6)

Patient Characteristics	*n* (%)
Age	
50–59 years	2 (33.3)
60–69 years	1 (16.6)
70–79 years	2 (33.3)
80+	1 (16.6)
Gender	
Male	4 (66.7)
Female	2 (33.3)
Marital Status	
Married	3 (50.0)
Widowed	1 (16.6)
Single	1 (16.6)
Diagnosis	
Dementia	6 (100)
Number of Medications (*n* = 6)	
Average (*SD*)	2.8 (1.6)
Range	1–5
Types of Medications[a]	
Antipsychotics	6 (100)
Anti-depressants	3 (50.0)
Anti-anxiety	4 (66.7)
Number of PRN Medications (n = 6)	
Average (*SD*)	1.7 (.98)
Range	0–3
Types of PRN Medications[a]	
Antipsychotics	4 (66.7)
Anti-depressants	2 (33.3)
Anti-anxiety	2 (33.3)
Falls Risk Assessment Tool Scores (*n* = 4)	
Morse Fall Scale[b]	
Average (SD)	77.5 (15.5)
Range	55–90
Classified as high risk, *n* (%)	4 (100)
Braden Scale[c]	
Average (*SD*)	13.5 (9.4)
Range	0–20
Classified as high risk, *n* (%)	2 (50.0)
Footwear Screen[d]	
Average (*SD*)	2.3 (3.3)
Range	0–7
Classified as high risk, *n* (%)	3 (75.0)

Note. **Percentages may not sum to 100% due to missing information. *SD* = standard deviation; PRN = "pro re nata" (as needed). [a]Percentages exceed 100% as some patients were prescribed more than one medication. [b]Scores range from 0–145; scores of 25 or less indicate a low risk of falls, scores of 26–49 indicate a medium risk of falls, and scores of 50 or greater indicate a high risk of falls (Morse et al., 1989). [c]Total scores range from 6–23; lower scores reflect lower levels of functioning and higher risk for pressure ulcers (Bergstrom et al., 1987). [d]Scores range from 0–7, with lower scores reflecting footwear that increases the risk for falls.**

HELPER System Performance

In total, the system ran for 267 device-nights, where a device-night was defined as a single fall detection device running for a single night (Table 4). Some of the rooms were not monitored for the full 12 weeks due to periods when the rooms were unoccupied or were occupied by unconsented patients, or due to technical difficulties with the system. Hospital PSRS records revealed that, of 28 recorded falls that occurred during

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Table 4: Number of nights the study ran in each patient room

Room	Number of Nights the Study Ran	Reason Some Nights were not Included
A100	90	N/A
A101	59	Technical difficulties
A102	78	Room was empty for 1.5 weeks
B100	19	No consented patient for most of the study period
B101	21	No consented patient for most of the study period

the study period, only one occurred in a room that was currently being monitored by the HELPER system; this was an injurious fall, resulting in a broken hip. The other 27 falls recorded in PSRS occurred in common areas or patient rooms not monitored by the HELPER system.

In total, four events captured by the HELPER system were categorized as falls (Table 5). These falls include one in which a person fell from a standing position onto the bed, and three where individuals fell or dropped quickly to the floor (one from a standing position, one from all fours, and one where a patient appeared to dive off the bed). In the latter two cases, it was difficult to discern whether the action was or was not intentional. There were nine boundary case events, which included two where the system detected a person lying on the floor but did not capture him getting there, one where a patient slumped farther and farther forward while sitting on the edge of the bed, coming precariously close to falling, and six where the system detected a patient on all fours on the floor. There were also 874 false alarms. The HELPER system did not detect the one fall reported in the PSRS in a room the system was monitoring at the time of the fall. Since the system detected four of the five known falls, sensitivity is found to be .80. Positive predictive value, defined as the percentage of alarms that resulted from actual falls, was quite low at .01 (4 falls + 9 boundary cases / 887 alerts).

Table 6 summarizes the types of events that triggered the false alarms. Twenty-six per cent of the false alarms resulted from image artifacts and technical difficulties, and another 38 per cent of the false alarms occurred

Table 5: The number of actual falls, detected falls, and false alarms from the HELPER system

	Falls	Boundary Cases	No Fall Occurred	Total
Alert raised	4 *(true positive)*	9	874 *(false positive)*	887
Alert not raised	1 *(false negative)*	N/A	N/A	

N/A = Not applicable

Table 6: Categorization of false positives (*n* = 874)

Event or Circumstances Triggering False Alarms	Occurrences, *n* (%)
Image artifacts and other technical difficulties	223 (25.5)
Nurse(s) present in the room	215 (24.6)
Beds moved out of the "safe zone"	113 (12.9)
Non-fall events that were not included in the training data	86 (9.8)
Non-fall events that were trained for but classified incorrectly	222 (25.4)
Non-fall boundary cases (e.g., dropped objects)	8 (0.9)
Reason for fall alert is unclear	7 (0.8)

either when nurses were present in the room or when beds had been moved out of their configured "safe zones". Examples of false alarms triggered by events that were not anticipated by the system (i.e., not included when training the machine-learning algorithms) included the bedroom door opening and closing, and the use of wheelchairs and walkers. Events that generated false alarms even though they were anticipated included people standing or walking in the room, and people bending over to pick up objects off the floor. Some interesting "near-miss" false alarms included clothes and pillows dropping to the floor, and towels or shoes moving on or near the floor.

Figure 1 presents a histogram illustrating the number of false alarms that occurred per device, per night. The average number of false alarms per night was 3.3 (*SD* = 4.9; mode = 0; median = 2), with a range of 0 to 35 per night. On nights when 14 or more false alarms occurred in a given room, this was almost always because the bed had gotten rotated 90 degrees so that it was outside its configured "safe zone", or there was a sustained time period when the camera produced corrupt images.

Nursing Staff Perceptions

Eleven nurses who had consented to participate in this study were invited to participate in the interviews; nine interviews were completed (81.8% response rate). One nurse declined because she was too busy, one declined because although she was participating in this study, she never had the opportunity to carry one of the study smartphones. The interviews ranged in length from 11 to 39 minutes and were on average 24 minutes in length (*SD* = 9.0).

All of the interview participants reported that they had ample opportunity to use the system, with almost all nurses reporting that they used it on all or most shifts they worked during the study time period (roughly three to four shifts per week); one participant noted that although she worked on many of the night shifts

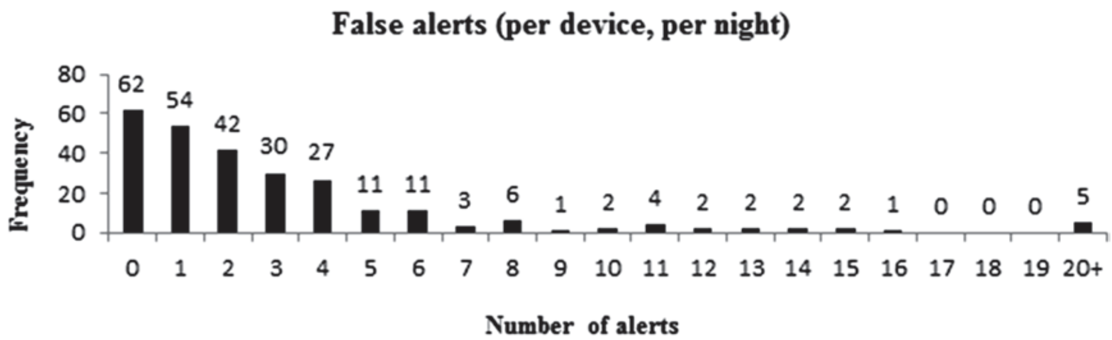

Figure 1: Histogram of false positives per device-night ($n = 874$)

during the study period, she estimated that she was actively involved in this study (i.e., carried the smartphone) for only about four shifts.

Nurses identified experience with a variety of different technologies as part of their clinical practice including assessment equipment (automatic blood pressure cliffs, digital thermometers); bed alarms, which are used for some patients to alert nurses when the patient is out of bed; HUGO (Healthcare Undergoing Optimization), an electronic system for ordering tests and prescribing and dispensing medications; WOWs (Workplace on Wheels), a mobile computer workstation that includes portable medical devices and medication dispensary; and emergency pagers. Reported personal use of technology included computers, laptops, and tablets; smartphones; and GPS (global positioning systems) devices.

The analysis of the interview transcripts generated five overarching themes, summarized here:

- Nurses are supportive of new technology that contributes to improvements in clinical practice and patient care, particularly when it functions as intended.
- While early detection is valuable, technology should focus on fall prevention.
- Fall-alerting mechanisms should be easy to use.
- The HELPER system has positive features over technologies that currently exist.
- Technological issues with the system and hospital infrastructure limit current usefulness in practice.

These themes are discussed in more detail in the following subsections.

Technology that Contributes to Improvements

Nurses are supportive of new technology that contributes to improvements in clinical practice and patient care, and, of course, when it functions as intended. Nurses generally reported that technology, in general, contributes to efficient use of time, less paperwork, and patient safety (e.g., HUGO reduces drug errors). However, when technology in general is not working properly, it was described as annoying, inconvenient, and was seen as something that made more work for them. Specific to the HELPER system, the high rate of false positive alerts was time-consuming as they had to check on patients and this was considered a "waste of time".

> WOWs [Workplace on Wheels] … if you made a mistake it can catch you or maybe it makes your job somewhat a little bit easier, but then on the other hand, if the computers are down then it's more work to do it. [ID5]

> Oh my goodness it's [HELPER system alarm] going off … you got the phone going off and you stop what you're doing, maybe you might be in the middle of doing an order or something and you have to stop that and go to see that, in fact, the patient was still in bed, right. It sort of wasted a lot of time. [ID9]

Nurses liked the concept, in principle, of having knowledge of a fall sooner than they would have otherwise, as, for example, when no one hears a fall or they come across someone who has fallen when they do their regular rounds of the unit, and thus, being able to respond immediately in the event of a fall. Nurses also anticipated potential system improvements, such as the possibility of alerting them of activity or movement within a patient room that may alert them to potential falls risks.

> If somebody fell [the alerts mean] that we could get to them sooner than later because around this time it gets kind of busy when we do snacks and give out meds. So sometimes if they're in their rooms and we're in the day room where it's sometimes hard to see [we don't know that they've fallen]. [ID5]

> I just liked the idea that if something was wrong, you knew sooner than you would have otherwise by making rounds. [ID4]

Technology Should Focus on Fall Prevention

Although there was general agreement that knowledge of a fall as soon as it occurs is optimal, nurses suggested that a better focus would be on the use of

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technology to prevent falls. They preferred to know of situations that increase the potential for falls, such as knowing when patients awoke in the night, were restless, or attempted to get out of bed, particularly patients identified at high risk for falls. Knowledge of patients' sleep and movement patterns was viewed as important to better understanding their potential risk for falls, and particularly when knowledge of medication doses and time of night can highlight factors that can contribute to fall risk. In this context, some of the false positive alerts that informed them of patients who were out of bed, but had not fallen, was considered valuable information. In these situations, they assisted the patient to navigate safely to washroom or back to bed.

> It alerted us when a patient was up. So that's good. We went and put the patient back to bed so it did do that. So at times it was useful because it alerted us that something was happening in the room so we went and checked, and other times it wasn't useful because there was nothing happening in the room and we would just dismiss it. Nothing was happening. [ID2]

> You can check on them sooner before they fall you know, if they're off you know, during the night, especially during the night if they're in bed and then all of a sudden you hear it ring and you know that they're off the bed and they shouldn't be off the bed because you don't want them to fall in the dark. [ID5]

Fall-Alerting Mechanisms Should Be Easy to Use

There was general consensus that the smartphone as an alerting mechanism was not ideal. It was noted that nurses already have too much to carry, so the smartphone was viewed as an added burden. It was also noted that for several nurses who did not use smartphones personally, some of the features were complicated. Additionally, in several situations nurses not familiar with the use of smartphones were found to have inadvertently altered some of the settings (volume, Wi-Fi access, connection to the HELPER devices), negatively affecting the proper functioning of the system.

> But the phone, it's just too much to carry in your pocket and it's too big and clunky … [ID6]

> Some people don't know how to work that [cell phone], if they don't have a cell phone. One girl said: 'I have no idea how to change the settings.' So she was carrying it all the time, but it wasn't going off because somebody had turned the volume down, and it wasn't alerting her so she would never check it because there was no way to tell her there was anything going on with it. [ID6]

One nurse noted her concern that family members would view her use of the smartphone negatively, perhaps thinking that staff were using it for personal purposes while on the job.

> So there's the nurse sitting in the office looking at the phone, and it's not your personal phone, but how are you going to prove that. Because to a family it looks like you're sitting there texting or something when in fact you're not. They have no idea that it has to do with the HELPER study. [ID6]

HELPER System: Advantages over Current Technologies

Interview participants identified a number of features of the HELPER system that they preferred over currently existing technology. Nurses particularly liked several features: the system was unobtrusive as it was embedded in the ceiling, the alert provided the room location so that they did not have to search out the location of the alert as they do with bed alarms, and the alert is not heard by patients, as the current bed alarm can be distressing for some patients.

> They [patients] didn't have a clue that there was something in the ceiling. [ID2]

> If you go close you hear the [bed] alarm going but you might have alarms in different beds … When we saw on the phone which room number, we go to the room number so we don't have to go from the beginning and check in each room. We would have wasted time catching it. … With the HELPER, I find that we go check the phone and it gives you right away [the room number], you don't waste time checking each room. [ID3]

Technological Issues and Hospital Infrastructure

In practice, the usefulness of HELPER in clinical practice was limited because of technical issues as well as issues involving hospital infrastructure. Although in theory the nurses liked the idea of the HELPER system, they reported that technological issues with the system and the hospital infrastructure (such as poor Wi-Fi connectivity) prevented their supporting the ongoing use of the system in its current state. The high rate of false alarms made more work for them with the consequence that they would turn the system off after repeated false alarms, particularly for patients who typically slept throughout the night. Due to the high rate of false alarms, they perceived that the system was not useful during peak care times such as bathing or dressing for bedtime.

> Well, the one night with [patient] it went off about 5-6 times and I said: 'She's sound asleep, let's just turn this off because this is too much.' She was sound asleep and she was a good sleeper. She slept right through the night. So there must have been a glitch or something … that one night where it went off 5 or 6 or 7 times in a row. That was annoying. [ID4]

The high false positive rate and limited accuracy in detecting falls resulted in nurses preferring bed alarms as a more accurate fall prevention technology despite their preference for the previously described features of the HELPER system.

> We had one client that has the HELPER program, and he would be walking down the hallway and it had never picked up that he'd even got out of bed and the night that the one gentleman did fall and break his hip, it didn't start to sound until we actually went in to attend to the gentleman that was on the floor that had the broken hip. So I would say no, I would put my faith in the bed alarms more so than this system. [ID7]

Discussion

This study adds to our understanding of the value of technology in the care of older adults, highlighting from the nurses' perspective those features that are most useful. Despite the technology producing a large number of false positives in this study, partially due to infrastructure issues that will be discussed later, nurses were receptive to the use of technology to detect, and preferably to prevent, falls; they would be interested in using the HELPER system again if improvements are made to the system. Several benefits to the use of the HELPER system, as opposed to the currently used bed alarms, were identified such as alerting nurses to the exact location of the potential fall; however, further refinement of the fall detection algorithm and further system training are needed to improve system capability and functionality related to fall detection. In this study, although nurses recognized the benefits associated with a rapid response to falls, they preferred access to information that could potentially assist in preventing falls, such as knowledge of when patients at high risk for falls were awake and attempting to leave their beds. In this setting, detecting sleep/wake patterns and motion in patient rooms may help clinical staff to prevent falls, by assisting non-ambulatory patients who get out of bed at night. Although devices exist that provide this information (Kelly et al., 2002; Cumming et al., 2008; Widder, 1985), there is limited data on their effectiveness in preventing falls and appropriateness with a patient population that is cognitively impaired, confused, or agitated.

In this pilot test of the HELPER system in a geriatric mental health hospital, the system failed to detect the one fall that was documented in the hospital PSRS as having occurred in a room in which the technology was installed. It cannot be known with certainty why the injurious fall was not detected because the system does not save images for review when it has not detected a fall. However, on the night of the fall, the camera in this room was delivering corrupted images which resulted in several false alarms, and it may have also contributed to the system's not detecting the fall that occurred. The HELPER system did detect four falls that were unknown to clinical staff and not documented in the PSRS, even in a closely monitored environment, suggesting that, first, the PSRS cannot be used as a gold standard and, second, the system's sensitivity can only be estimated. In these cases, it is possible that those who fell were not injured and did not require assistance to get up, and as such these falls were not witnessed by, and remained unknown to, nursing staff. Although the system sent alerts to the smartphones for these falls, as will be discussed later, there are a number of potential reasons why the nurses did not receive these alerts, including poor Wi-Fi connectivity and nurses' not utilizing the phones as expected, especially during busy patient care periods.

Table 2 presents results from other fall detection studies conducted in natural environments. HELPER's sensitivity (.80) fared well in comparison to most of these systems, but its false alarm rate (3.3/day on average) was worse than most. Studies conducted in laboratories are not comparable since those systems run under carefully controlled conditions and for very brief time periods. Many complications arising from the real-world nature of this study contributed to the high false alarm rate and are discussed more fully below. Notably, 25.5 per cent of the false alarms produced by the HELPER system were the result of technical difficulties. This prototype system was custom-built to meet the demanding challenges of the real-world problem, including the need to operate at night, to minimize areas within the room that are occluded from view, and to cover the entire room with a single device to minimize cost. Recent studies using the commercially available Kinect sensor have reported significantly fewer false alarms, but the Kinect suffers from a relatively narrow field of view and may require more devices per room (Stone & Skubic, 2015). Although this is unlikely to change, the technical difficulties experienced by HELPER can likely be overcome as the technology matures.

Evaluating fall detection technology in a real-world environment presented a number of significant challenges that are generally not present in laboratory-based evaluations; lessons learned in this study will serve to enhance further development of the technology and improve implementation of future studies. When the real-world test settings are at a distance for the research team developing the technological devices, immediate troubleshooting and regular maintenance tasks are more difficult to implement and there are limited informal training opportunities that would serve to promote proficiency and comfort with the devices among the clinical staff and evaluation study research team. Regular and sufficient opportunities for communication among the research teams (laboratory and evaluation study) and clinicians may serve to better resolve technological issues as they arise.

In addition, real-world deployment of technology requires sensitivity to the needs of end users and infrastructure issues, which can result in technical challenges not present in the laboratory setting. To reduce potential discomfort for patients with paranoia, the fall detection devices were installed above the ceiling, with only a small acrylic panel visible from within the room. This posed a challenge because the drop-down ceiling panels were metal, creating a significant barrier to Wi-Fi access; the unreliability of the Wi-Fi communication between the fall detection devices and smartphones meant that some rooms could not be used in this study, precluding use with some patients at high risk for falls. Moreover, the poor Wi-Fi connection made it difficult for the laboratory research team to access the devices remotely, delaying resolutions of problems and regular maintenance tasks. In addition, a set of heating pipes that ran just above the centre ceiling panel in each room negatively impacted the functionality of one device when the metal camera mount touched the metal pipes. These technical issues resulted in frustration among the nursing staff, whose busy schedules require the technologies they work with to be reliable and predictable.

The development of technological devices for use in clinical settings requires a thorough knowledge of the types of activities that occur in these settings. In developing the machine learning algorithms for the system, the amount of movement anticipated in patient rooms at night was greatly underestimated. Assumptions were made that patients would mostly remain in bed or get up in the night to walk within the room or to the washroom. However, in reality patients were quite active, sometimes leaving their own rooms to wander the unit or other patient rooms, and there was also much nursing activity. Had this higher level of activity been accounted for in the machine learning algorithms created for the system, this might have reduced the number of false alarms. False alarm rates were also affected by changes in furniture placement, which altered how the device understood "safe zones" in the room not likely to be associated with a fall. Frequent changes in furniture location will require a more robust technological solution than pre-configured safe zones to exclude the bed from fall alerts; more research is required to solve this difficult problem. In addition, nurses' movement and activity in the room when they were providing care resulted in a large number of false alarms. Their failure to "pause" the system during these times suggests a potential improvement would be to have the devices automatically detect the presence of nursing staff and turn off system monitoring while personal care is being provided.

Although smartphones were selected as alert receivers in the HELPER system because apps for this purpose are relatively easy to write and because it was assumed that most people would be comfortable with their use, in practice the nurses did not find the smartphones convenient. Some found them bulky, some found their settings confusing, and at least one objected to the possibility of being seen using the phone by people who would not understand it was work related. This may have resulted in nurses' not always carrying the phones and in the phones' volume or other settings being incorrectly set, which may in turn have resulted in nurses not receiving all the alerts that were sent by the system. Indeed, this might explain why the nurses were unaware of the four falls that were correctly detected by HELPER over the course of the study but not documented in the hospital's PSRS system.

In the current study, the high rate of false alarms reduced nursing staff interest in sustaining the use of this technology. A review of sensor-type systems to prevent falls concluded that high rates of false alarms can desensitize staff to the alarms, thereby reducing their response time to such alarms and act as a barrier to full integration into clinical care (Kosse, Brands, Bauer, Hortobagyi, & Lamoth, 2013). Our experience in this study has demonstrated the usefulness of obtaining nursing staff perceptions of new technology following trialed use in order to obtain information that will facilitate improvements to system performance and that addresses their issues in using this type of technology in clinical practice to improve patient care.

Automatic video-monitoring-based fall detection is beneficial in a geriatric psychiatry setting as it requires no intervention on the part of the patient (in contrast to personal emergency response systems that may require the fallen patient to push a button for assistance), and it is generally non-intrusive in that no devices need to be worn. Moreover, video-monitoring-based fall detectors may have the potential to identify variations in movements, such as unusual activity that could potentially lead to a fall. However, ethical concerns about privacy intrusion from video monitoring must also be considered.

Although it has been argued that depth images are more protective of privacy than are colour or infrared images (Zhang et al., 2014), this position is debatable. Depth images do make it difficult to visually identify the individual being monitored, but when the monitoring device is placed in individual patient rooms or installed in homes, the identity of the monitored individual is already known. A more urgent concern is to ensure that the video monitoring does not become video surveillance where the activities within the monitored areas can be watched by third parties. This is equally necessary regardless of image type. The strongest privacy assurance would come from processing the images in real time and discarding them immediately so that they are never accessible to human eyes.

Limitations and Future Directions

This study has a number of limitations. During the study time period, there were a low number of falls (n = 5) in the study setting, which limited the robustness and generalizability of the performance results. It also limited the opportunities for nurses to experience the full scope of the technology and to learn how the technology performs in real fall situations; this, too, reduces the generalizability of our findings. Many of the technological challenges experienced in this study were related to infrastructure issues in the study setting, limiting the generalizability of these findings to settings which may not have the same infrastructure issues. In addition, in some instances nursing staff did not follow the study protocol related to the time period in which the HELPER system was to be operational.

Although the system was to be operational nightly starting at 7:00 p.m., nursing staff frequently chose to turn off or not carry the HELPER system smartphones until 9:00 or 10:00 p.m., after patients had settled into bed for the night. Early evenings were described as very busy with patients needing to be fed, bathed, given medications, and put to bed. The nurses preferred not to be interrupted from these tasks to respond to HELPER system alerts, especially given the system's high rate of false alarms. Given this, it might have been more appropriate for the HELPER system to begin monitoring at a later hour, or perhaps to begin in each room when the patient in that room went to bed. Doing so could have improved nurses' buy-in of the project and could also have reduced the number of false alarms, since these frequently occurred when there were multiple nurses and a lot of early evening activity in the room. Moreover, there may be a selection bias in nurses who volunteered to use the technology in this study; their perspectives may not be representative of all nursing staff within these units.

Further development of the HELPER system will address the technological and implementation issues described, focusing on reducing the occurrence of false alarms and ensuring that it meets the needs of end users. Combining video imaging technology with other sensor modalities could improve performance, and providing additional information to nursing staff such as an image of the room accompanying a fall alert could reduce the disruptiveness of false alarms. We are currently developing a version of the system for home use that attempts to engage the fallen person in an audio conversation to determine whether and what sort of assistance is needed. This approach can provide comfort to older adults living alone, as well as mitigate the disruptiveness of false alarms (Mihailidis et al., U.S. Patent No. 8.063,764, 2011). Analysis of system images obtained in the last few minutes preceding a fall can potentially be useful for learning about the human and environmental factors that lead to falls.

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