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Fall Detection Devices and their Use with Older Adults: A Systematic Review

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Abstract

Background—Falls represent a significant threat to the health and independence of adults 65 years of age and older. As a wide variety and large amount of passive monitoring systems are currently and increasingly available to detect when an individual has fallen, there is a need to analyze and synthesize the evidence regarding their ability to accurately detect falls to determine which systems are most effective.

Objectives—The purpose of this literature review is to systematically assess the current state of design and implementation of fall detection devices. This review also examines the extent to which these devices have been tested in the real world as well as the acceptability of these devices to older adults.

Data sources—A systematic literature review was conducted in PubMed, CINAHL, EMBASE and PsycINFO from their respective inception dates to June 25, 2013.

Study Eligibility Criteria and Interventions—Articles were included if they discussed a project or multiple projects involving a system with the purpose of detecting a fall in adults. It was not a requirement for inclusion in this review that the system targets persons over the age of 65. Articles were excluded if they were not written in English or if they looked at fall risk, fall detection in children, fall prevention or a Personal Emergency Response device.

Study appraisal and synthesis methods—Studies were initially divided into those using sensitivity, specificity or accuracy in their evaluation methods, and those using other methods to evaluate their devices. Studies were further classified into wearable devices and non-wearable devices. Studies were appraised for inclusion of older adults in sample and if evaluation included real world settings.

Results—This review identified 57 projects that used wearable systems and 35 projects using non-wearable systems, regardless of evaluation technique. Non-wearable systems included cameras, motion sensors, microphones and floor sensors. Of the projects examining wearable systems, only 7.1% reported monitoring older adults in a real world setting. There were no studies of non-wearable devices that used older adults as subjects in either a lab or a real world setting. In general, older adults appear to be interested in using such devices although they express concerns over privacy and understanding exactly what the device is doing at specific times.

Limitations—This systematic review was limited to articles written in English and did not include gray literature. Manual paper screening and review processes may have been subject to interpretive bias.

Conclusions and implications of key findings—There exists a large body of working describing various fall detection devices. The challenge in this area is to create highly accurate unobtrusive devices. From this review it appears that the technology is becoming more able to accomplish such a task. There is a need now for more real world tests as well as standardization of the evaluation of these devices.

Keywords

Falling; Elderly; Monitoring

Introduction

Adults 65 years of age or older experience higher rates of falling and are generally at a higher risk for falls. ¹⁻⁴ One in every 3 persons over the age of 65 years are estimated to fall 1 or more times each year. ⁵⁻⁷ Falls and fall related injuries represent a significant threat to the health and independence of adults 65 years of age and older. Falls can have severe consequences such as injury or death; in 2010 in the United States, 21,649 older adults died from fall related injuries. ⁸ Even if a fall does not result in a physical injury, it can often produce fear of falling resulting in a decrease in mobility, participation in activities, and independence. ^{9, 10} Fear of falling can be amplified in the presence of the “long lie”, which is identified as involuntarily remaining on the ground for an hour or more following a fall. ¹ Such an event can result in substantial damage to the individual’s body and morale. Lying on the floor for an extended period of time often results in several medical complications such as dehydration, internal bleeding, pressure sores, rhabdomyolysis or even death. Half of those who experience the “long lie” die within 6 months of the fall. ¹¹ A recent cohort study reported a “long lie” was seen in 30% of fallers; ¹² therefore it represents a great threat to the long term health of older adults.

Evidence-based methods to prevent falls include regular exercise, vitamin D supplementation and having regular fall risk assessments. ^{2, 13-15} However, despite prevention efforts falls are still likely to occur as one ages, and they need to be quickly identified to prevent further injury to the fallen individual. Personal emergency response systems or PERS represent one commercial solution to addressing this issue. These clinical alarm systems provide a way for individuals who fall to contact an emergency center by pressing a button. ¹⁶ While appropriate in many situations, the PERS system is rendered useless in the event that the person is unconscious or unable to reach the button. Even when the system is available, a recent cohort study found that around 80% of older adults wearing a PERS did not use their alarm system to call for help after experiencing a fall. ¹²

Due to these challenges associated with PERS systems, passive monitoring solutions have been proposed to more accurately detect falls. Several solutions are currently available with most being devices worn by a person (e.g. as a wristwatch or attached to clothing). Other solutions include technologies embedded in the residential setting such as cameras, microphones or pressure sensors installed underneath the flooring. Previous fall detection literature reviews have dealt with the principles of fall detection, the ethical issues associated with these systems or the practicality of such systems. ¹⁷⁻²⁰ However, with the

wide variety and sheer number of available systems there is a need to synthesize the evidence of their ability to accurately detect falls.

Fall detection technologies enable rapid detection and intervention for individuals who have experienced a fall. This ability could reduce the physical and mental damage caused not only by the fall but time after a fall before discovery. These technologies will help to reassure those at a risk of falling as well as their caregivers and family. In the future, these devices can help physical therapists and other clinicians to clearly understand not only when the person experienced the fall, but also circumstances surrounding the fall, allowing for better treatment of the individual in question.

The primary aim of this paper is to review the evidence on fall detection devices and to analyze their level of success in automatically detecting falls. Secondary aims of this review are to examine older adults' usage and perceptions of these devices as well as the implementation of these devices in "real world" situations. "Real world," as we define it for the purposes of this review, is a certain period of time in which subjects use the device in their normal environment without any instructions given by the researcher. Simulating falls or activities of daily living (ADLs), as instructed by the researcher, in one's home would not be viewed as a "real world" situation for purposes of this review.

Methods

The systematic literature review was conducted in PubMed, CINAHL and EMBASE and PsycINFO from their respective inception dates to June 25, 2013. See Appendix A for detailed search strategy used for one of the databases.

We included articles in this review if they discussed a project or multiple projects involving a system with the purpose of detecting when an adult has fallen (including studies ultimately designed for use with adults but with laboratory tested "subjects" i.e. dummies simulations, actors). While we examined systems designed for adults it was not a requirement for inclusion in this review that the system specifically target adults over the age of 65. However, we did exclude systems that targeted children due to differences in fall patterns between children and adults. We excluded articles if they were literature reviews or if they looked at fall risk, fall detection in children, fall prevention or a PERS device.

The criteria for inclusion or exclusion were finalized by the team, and the primary search was carried out by the first author (S.C). Article selection was conducted by the first author who reviewed full texts of the relevant articles using a data extraction spreadsheet developed for this review. In order to ensure reliability of article selection, two of the authors (G.D., H.T.) blindly and independently assessed a subset of articles from the initial search for the appropriateness of inclusion in the final review. There was full agreement between all authors on articles selected for inclusion.

Quality scoring was conducted using the Statement on Reporting of Evaluation Studies in Health Informatics (STARE-HI).²¹ In order to account for the variety of manuscripts, a condensed version of the STARE-HI was used which included 3 items deemed most important in the mini-STARE-HI^{22, 23} as well as 3 additional criteria. 1) Description of how

the system works, 2) Baseline demographic data/characteristics of participants, and 3) Basic outcome numbers (e.g., number of fall events, types of events, etc.). If the manuscript did address the criterion, they were given a score of 1, if they did not they were given a score of 0. Thus the possible range of quality score is 0–6 with a 6 indicating the paper addressed all of the STARE-HI quality criteria. In order to ensure reliability of quality scoring, one of the authors (H.T.) blindly and independently scored a random subset of articles. Differences in scoring were discussed and corrected before a final round of scoring was conducted.

The initial search yielded 617 results from which all abstracts were read to further determine eligibility for this review. Five hundred and sixteen papers found in the initial search did not focus on fall detection but instead focused on various topics from gait, balance and posture to seizures and medical instrumentation. These papers were eliminated leaving a total of 101 unique papers to be read in full. Scanning the reference lists of these papers allowed for the identification of 24 more papers that dealt primarily with fall detection, for a total of 125 papers. In reading the full texts, 12 dealt with children, fall risk, fall prevention or a PERS device and were excluded from this review. Of the remaining 113 papers, 31 did not attempt to evaluate their system based on accuracy, sensitivity or specificity of a detection device. Figure 1 fully diagrams the literature identification and screening process.

Results

The results section is divided into 3 parts. It first provides an overview of currently available systems and their classifications. Then, for ease of comparison, the next 2 sections are divided into projects which used measures of sensitivity, specificity or accuracy to evaluate their device and projects which used other methods to evaluate the device.

Current state of fall detection systems

The various existing detection devices can be divided into wearable and non-wearable systems. Wearable systems generally consist of placing an accelerometer upon the subject which can detect changes in acceleration, planes of motion or impact in order to detect falls.^{24–26} Non-wearable systems include cameras,^{27–29} acoustic sensors^{30, 31} and pressure sensors³² that are placed in the subject's normal environment and use various measurements to determine if the subject has fallen. From this review, we identified 57 projects using wearable systems and 35 projects involving non-wearable systems (regardless of evaluation technique and not including projects using multiple systems).

Projects evaluating the device based on accuracy, sensitivity or specificity

Eighty-two papers described some method of device testing which included sensitivity, specificity or accuracy. These were further categorized by the different kind of sensors they were describing. Some papers described the results and procedures resulting from the same project.^{24, 33–48} For the purpose of this analysis, we took their findings into account only once, resulting in 74 total projects.

Forty-two of these projects discussed the use of wearable sensors. Non-wearable devices included 16 projects using cameras or motion sensors, 4 projects using microphones, and 2 projects which used a floor sensor. There were also 10 projects which used multiple sensor

systems to detect if a person had fallen. Multiple sensors, as we have defined them, can be any combination of 2 or more sensor types used to monitor a subject. Tables 1 through 3 list specific details about the various projects including how the researchers defined their subjects and their stated values for accuracy, sensitivity or specificity. Medians of accuracy, sensitivity and specificity are presented throughout the following sections. Some were difficult to determine as many projects either did not provide a value or provided a range of values depending on the number of tests conducted for various types of falls (falling forwards, falling backward, etc.) The medians presented are taken only from papers that provided a single overall value for each element (i.e., papers using ranges or declaring multiple values for each fall types were not included in the calculation of a median). This does not account for many variables including year of the project or testing procedure and thus should not be used to compare the success of different device types and are meant only to provide a high level view of how each type of device performs.

By definition, most of the projects involving wearable devices placed their sensor onto their subject and tested them either in a simulated or real world environment (Table 1). Many papers attempted to identify a fall by impact, although there were also papers whose aim was to detect a fall pre-impact. When measuring impact, one has to measure the vibration of the impact through the body which could cause some inaccuracies. By measuring falls pre-impact, one is able to avoid this as well as any scenario where the device is damaged due to the fall. Also by measuring falls pre-impact it may be possible in the future to prevent falling injuries by using additional equipment such as airbags which would inflate right before the fall. Some of the wearable device projects compared the pre-impact fall detection capabilities of their system to that of a camera system.^{36–38, 49} These projects were only using camera systems as a tool for comparison and thus were not listed under multiple sensors. Another example of such a project compared the accuracy of a cell phone to the accuracy of a device solely used for fall detection.⁵⁰

About 19% of the wearable projects reported utilizing older adults to test their device in a controlled environment while only 7.1% reported monitoring older adults under real world settings.^{25, 33, 34, 51, 52} The rest of the studies mostly used healthy young subjects who were volunteers, actors or participants in the study. Thirty-five of the projects used a single device while 4 projects used 2 separate devices and another 4 projects used 3 separate devices. The most common location for these devices was the trunk of the body (chest, waist, thorax, etc.). Other devices were placed near the head, arms, hands or feet of the subject. Systems with the device centering on the trunk had a median sensitivity of 97.5% (range 81–100) and a median specificity of 96.9% (range 77–100). Those involving multiple sensors had a median sensitivity of 93.4% (range 92.5–94.2) and a median specificity of 99.8% (range of 99.3–100). Finally the devices placed around the arm, hands, ears or feet had a lower median sensitivity and specificity [81.5% (range 70.4–100) and 83% (range 80–95.7) respectively] when compared to other sensors. Median accuracy was not available for all 3 categories of sensors and thus is not provided here.

Non-wearable devices were often set up in a room where the subjects would either walk around or live in for some amount of time (Table 2). While some real world applications of these projects exist, surprisingly there were no projects which explicitly stated using older

adult subjects even in a controlled setting. The most common non-wearable systems involved cameras or motion detectors. These 2 device types are grouped together as it can be hard to differentiate them based on the descriptions given by the researcher. Usually a motion detector involved infrared sensors that identify motion, while cameras provided full images. Most of the projects used single cameras in their trials although 4 did specifically state that they used multiple camera networks.^{86–88} Most of the cameras were stand-alone, however 1 study did require the subjects to wear reflective sensors on their body so that the camera could better identify them.⁸⁸ The median accuracy for cameras was 96.6% (range 77–100) while the median sensitivity and specificity were 93% (range 66.7–100) and 98.5% (range 87.5–100) respectively.

All 4 of the microphones systems used a robust array of microphone system, FADE, which was able to detect the 3-D sound source location.^{30, 31, 89, 90} Of these 4 projects, a single project reported an accuracy of 100%, 2 reported sensitivities of 100% and 1 reported a specificity of 97%. The 2 floor sensors listed in this category have median sensitivities and specificities of 95.4% (range 90.7–100).^{32, 91} However floor sensors were generally used in combination with other sensors.

Multiple sensor projects used various combinations of systems to detect a fall (Table 3). Papers which compared their systems to another system were not included in this category. Most of these projects were fairly recent and were implemented with the goal of more accurately measuring a fall by evaluating multiple signals. These projects had a surprisingly small number of human participants with some using computer generated falls or using anthropomorphic dummies for falls. However, 3 more recent projects have been tested with older adults in real world environments, a single study completed within their homes¹⁰⁰ and 2 in a clinic setting.^{44, 52}

Table 4 provides a high level comparison between the different types of devices. The average number of subjects and the types of subjects involved were taken only from papers which clearly defined their samples and excluded any simulated data or fall dummies. As with earlier medians and ranges, these numbers should be interpreted cautiously as they do not account for many variables in the evaluation process including number of trials, number of subjects, types of falls etc.

Projects evaluating their device in other ways

Thirty-one papers did not provide information on sensitivity, specificity or accuracy of the fall detection systems under study. These papers described either various design implementations of a system, or results from various focus groups, case studies, interviews or observational studies on a fall detection device. Twenty-two papers focused on the design of their devices describing in detail how the device works, how it is to be used and/or various methods for identifying falls. Of these designs, 11 devices were wearable with 1 even featuring a pre-emptive airbag.^{107–117} Other devices involved wireless motion sensors or cameras^{118–126} and phone applications.^{127, 128}

Two papers used their fall detection devices in comparative studies. One compared the acceleration of simulated falls to that of real world falls.¹²⁹ They found many similarities

between real life falls of older adults and experimental falls of middle aged subject although some characteristics from experimental falls were not detectable in real life falls. The other study compared residential communities with and without a fall detection system. Outcomes of interest were incident falls, hospitalizations, changes in needed level of care and resident attrition.¹³⁰ The authors found there were fewer falls per week, fewer weekly hospitalizations per week and a higher resident retention rate at the facility with the fall detection device.

The remaining 7 papers used various methodologies to elicit feedback from subjects on the feasibility of emerging or existing fall detection devices. Two studies used focus groups or questionnaires to help guide the development of a new fall detection device by suggesting various design specifications for their sensor systems.^{131, 132} Another study used volunteers to gauge the feasibility of using a carpet sensor.¹³³ Other studies were more interested in the perceptions of older adults regarding fall detection devices. One study conducted a trial of an extended fall detection system vs. a standard pendant alarm and interviewed the subjects after the trial.¹³⁴ Older adults found that the use of telemonitoring gave them a greater sense of security and enabled them to remain at home. However, some found the device intrusive and did not feel they were in control of alerting the call center. Another study used structured interviews to look at older adults perceptions of having a video monitoring system in their home.¹³⁵ While they reported that 96% of their participants felt favorably towards the system, only 48% said they would actually use it. Another paper showed various groups of subjects videos of different types of falls.¹³⁶ They then proceeded to discuss the issues of falling and system designs with the subjects. Many of the subjects stated their desire for more passive fall detection systems and most wanted to have the ability to know exactly what the system was doing at all times. The final paper described the results of focus groups and a pilot study.¹³⁷ The focus groups discussed the potential for fall technologies with both adult users and health care providers, revealing neither group were all that receptive to the idea of fall detectors. The pilot study was used to gain insight into the effect of fall detectors on fear of falling. In this study they measure the participants' fear of falling using the Falls Efficacy Scale pre- and post-test. They found that the use of a detector did reduce the level of fear for 1 group but this reduction was not significant.

Discussion/Conclusion

An extensive body of work has been conducted in the area of fall detection using a variety of solutions. These devices can measure different aspects of the fall from velocity to impact and even the posture of the faller. Each type of device appears to have its own strengths coupled with certain weaknesses.

Wearable devices for example, if used properly are always with their subjects and can easily detect the acceleration or impact experienced by the subjects. However, these devices are reliant on the subject not only remembering to wear the device but also choosing to wear the device which can be especially difficult at nighttime.^{17, 42, 87, 106, 107} These devices are also dependent on battery power and can suffer from false alarms due to impact or changes in acceleration not caused by falls. Non-wearable systems on the other hand do not rely on the subject to remember to use the system. Instead they are able to survey a certain area while

hardly affecting the individual. However these systems are limited to a specific space and suffer from aspects of privacy concerns.^{29, 87} Cameras, with their ability to take full photos or videos of their subjects, have been seen as too intrusive. These systems suffer from problems with occlusion (having the subject blocked by another object in the room) and being limited to indoor locations.⁴¹ One solution to both these issues is using multiple sensors to account for the weaknesses in each device. For example, coupling a passive camera system with a wearable system would account for the subject leaving the space of the camera or the subject forgetting to wear the device at night. However, adding more and more devices could overwhelm the older adult causing them to reject such systems.

Studies have shown that older adults want to be able to live at home and are more or less willing to accept new technologies that support their independence.^{137, 138} When dealing with fall detection technologies, many studies have shown that older adults are favorable to such systems and find that the use of these devices can give them a greater sense of security.^{134–137} At the same time however, some older adults found such devices intrusive, were annoyed by false alarms and stated their desire for more passive systems along with an ability to know what the system was doing at all times.²⁵ The challenge in this area of work is to create highly accurate devices that are as unobtrusive as possible. From this literature review, it appears that the technology is becoming more available to accomplish such a task. What is needed now is further testing of such devices in real world settings.

As our review and previously published literature suggest, very few long-term real world tests of such devices have been documented.^{25, 33, 34, 44, 100, 129, 139, 140} Multiple commercial fall detection devices are publicly available, but their accuracy is hard to identify. Real world tests can be difficult as they can often take a large amount of resources and time. It may also be difficult to recruit for such studies as older adults at risk of falling may also be more likely to be cognitively impaired or have a shorter life span.¹⁴¹ Such difficulties were experienced in a recent study by Gietzelt et al. who noted of 3 subjects it was only possible to interview 1.¹⁰⁰ This was because of a death of a subject and the other subject developing a significantly impaired cognitive status which precluded interview.

One way to ease the challenge of real world testing may be to expand eligibility criteria allowing for healthier older adults to join the study. However, this reduction could also be a disadvantage as it may result in fewer fall events. Boyle et al. tried to use real time data with 15 adults over the course of 300 days and was only able to record 4 falls during that time.⁵⁹ Real world tests however, have been shown to be a more rigorous indicator of the device's accuracy than simulated testing.^{52, 139, 140} Even with the aforementioned challenges, more real world tests are needed to prove the efficiency of these devices and to improve the health of the individuals these devices are made for. Suggestions for future research that may overcome these challenges include careful selection of subjects to include individuals most likely to benefit from the devices, those at high risk for falls. This includes community dwelling older adults with a fall in the previous year, or those with gait or balance disturbances that put them at high risk for fall.

Adding more real world testing may make it more difficult to standardize the evaluation process of such devices; however, it is difficult to compare the various measurements of

accuracy between devices as there is no common method for evaluating such devices. As has already been suggested, evaluating fall detection devices needs to become more standardized to be able to properly evaluate the strengths and weaknesses of the currently available devices.¹⁷ One way to do this would be to have a subject live in a simulated environment for a certain period of time; this would allow for standardization across subjects while still providing real world data.

Limitations

This review was limited to articles written in English and indexed in PubMed, CINAHL, EMBASE or PsycINFO and as such may have omitted other relevant published studies. Also, as with any systematic literature review, manual paper screening and review processes may have been subject to interpretive bias.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

References

1. Lord, SR.; Sherrington, C.; Menz, HB. Falls in older people: risk factors and strategies for prevention. Cambridge, U.K: Cambridge Univ. Press; 2001.
2. Tinetti ME. Clinical practice. Preventing falls in elderly persons. *N Engl J Med.* 2003; 348(1):42–49. [PubMed: 12510042]
3. Stevens JA, Mack KA, Paulozzi LJ, Ballesteros MF. Self-Reported Falls and fall related injuries among persons aged >65 years. *J Safety Res.* 2008; 39(3):345–349. [PubMed: 18571577]
4. Hausdorff JM, Rios DA, Edelberg HK. Gait variability and fall risk in community-living older adults: a 1-year prospective study. *Arch Phys Med Rehabil.* 2001; 82(8):1050–1056. [PubMed: 11494184]
5. Tinetti ME. Prevention of falls and fall injuries in elderly persons: a research agenda. *Prev Med.* 1994; 23(5):756–762. [PubMed: 7845954]
6. Center for Disease Control and Prevention. [Accessed 1/ 11/2013] Falls among older adults: an overview. <http://www.cdc.gov/HomeandRecreationalSafety/Falls/adultfalls.html>
7. Hausdorff JM, Rios DA, Edelberg HK. Gait variability and fall risk in community-living older adults: a 1-year prospective study. *Arch Phys Med Rehabil.* 2001; 82(8):1050–1056. [PubMed: 11494184]
8. Center for Disease Control and Prevention. [Accessed 4/2/2013] Injury Prevention and Control: Data & Statistics (WISQARS). http://www.cdc.gov/injury/wisqars/fatal_injury_reports.html
9. Ozcan A, Donat H, Gelecek N, Ozdirenc M, Karadibak D. The relationship between risk factors for falling and the quality of life in older adults. *BMC Public Health.* 2005; 5:90. [PubMed: 16124871]
10. Sattin RW, Lambert Huber DA, DeVito CA, et al. The incidence of fall injury events among the elderly in a defined population. *Am J Epidemiol.* 1990; 131(6):1028–1037. [PubMed: 2343855]
11. Wild D, Nayak US, Isaacs B. How dangerous are falls in old people at home? *Br Med J (Clin Res Ed).* 1981; 282(6260):266–268.
12. Fleming J, Brayne C. Inability to get up after falling, subsequent time on floor, and summoning help: prospective cohort study in people over 90. *BMJ.* 2008; 337:a2227. [PubMed: 19015185]
13. Feder G, Cryer C, Donovan S, Carter Y. Guidelines for the prevention of falls in people over 65. The Guidelines' Development Group. *BMJ.* 2000; 321(7267):1007–1011. [PubMed: 11039974]
14. Gillespie LD, Gillespie WJ, Robertson MC, Lamb SE, Cumming RG, Rowe BH. Interventions for preventing falls in elderly people. *Cochrane Database Syst Rev.* 2003(4) CD000340.

15. Campbell AJ, Robertson MC, Gardner MM, Norton RN, Tilyard MW, Buchner DM. Randomised controlled trial of a general practice programme of home based exercise to prevent falls in elderly women. *BMJ*. 1997; 315(7115):1065–1069. [PubMed: 9366737]
16. Porter EJ. Wearing and using personal emergency response system buttons. *J Gerontol Nurs*. 2005; 31(10):26–33. [PubMed: 16262088]
17. Noury N, Fleury A, Rumeau P, et al. Fall detection--principles and methods. *Conf Proc IEEE Eng Med Biol Soc*. 2007:1663–1666. [PubMed: 18002293]
18. Ward G, Holliday N, Fielden S, Williams S. Fall detectors: a review of the literature. *J Assist Technol*. 6(3):202–215.
19. Stewart LSP, McKinstry B. Fear of falling and the use of telecare by older people. *Br J Occup Ther*. 2012; 75(7):304–312.
20. Ganyo M, Dunn M, Hope T. Ethical issues in the use of fall detectors. *Ageing Soc*. 2011; 31(8): 1350–1367.
21. Talmon J, Ammenwerth E, Brender J, de Keizer N, Nykänen P, Rigby M. STARE-HI--Statement on reporting of evaluation studies in Health Informatics. *Int J Med Inform*. 2009; 78(1):1–9. [PubMed: 18930696]
22. de Keizer NF, Talmon J, Ammenwerth E, Brender J, Nykanen P, Rigby M. Mini Stare-HI: guidelines for reporting health informatics evaluations in conference papers. *Stud Health Technol Inform*. 2010; 160(Pt 2):1206–1210. [PubMed: 20841875]
23. de Keizer NF, Talmon J, Ammenwerth E, Brender J, Rigby M, Nykanen P. Systematic prioritization of the STARE-HI reporting items. An application to short conference papers on health informatics evaluation. *Methods Inf Med*. 2012; 51(2):104–111. [PubMed: 21373719]
24. Bourke AK, O'Brien JV, Lyons GM. Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm. *Gait Posture*. 2007; 26(2):194–199. [PubMed: 17101272]
25. Bourke AK, van de Ven PW, Chaya AE, O'Laughin GM, Nelson J. Testing of a long-term fall detection system incorporated into a custom vest for the elderly. *Conf Proc IEEE Eng Med Biol Soc*. 2008:2844–2847. [PubMed: 19163298]
26. Kangas M, Vikman I, Wiklander J, Lindgren P, Nyberg L, Jämsä T. Sensitivity and specificity of fall detection in people aged 40 years and over. *Gait Posture*. 2009; 29(4):571–574. [PubMed: 19153043]
27. Belshaw, M.; Taati, B.; Giesbercht, D.; Mihailidis, A. Intelligent Vision-Based Fall Detection System: Preliminary Results from a Real World Deployment; Toronto Canada. Paper presented at RESNA/ICTA 2011: Advancing Rehabilitation Technologies for an Aging Society; Jun 5–8, 2011;
28. Belshaw M, Taati B, Snoek J, Mihailidis A. Towards a single sensor passive solution for automated fall detection. *Conf Proc IEEE Eng Med Biol Soc*. 2011:1773–1776. [PubMed: 22254671]
29. Sixsmith A, Johnson N. A smart sensor to detect the falls of the elderly. *IEEE Pervasive Comput*, IEEE. 2004; 3(2):42–47.
30. Li Y, Zeng Z, Popescu M, Ho KC. Acoustic fall detection using a circular microphone array. *Conf Proc IEEE Eng Med Biol Soc*. 2010:2242–2245. [PubMed: 21096795]
31. Popescu M, Li Y, Skubic M, Rantz M. An acoustic fall detector system that uses sound height information to reduce the false alarm rate. *Conf Proc IEEE Eng Med Biol Soc*. 2008:4628–4631. [PubMed: 19163747]
32. Alwan, M.; Rajendran, P.J.; Kell, S., et al. A Smart and Passive Floor-Vibration Based Fall Detector for Elderly; Damascus, Syria. In: 2nd International Conference on Information and Communication Technologies; Apr 24–28 2006;
33. Bourke AK, van de Ven P, Gamble M, et al. Assessment of waist-worn tri-axial accelerometer based fall-detection algorithms using continuous unsupervised activities. *Conf Proc IEEE Eng Med Biol Soc*. 2010:2782–2785. [PubMed: 21095967]
34. Bourke AK, van de Ven P, Gamble M, et al. Evaluation of waist-mounted tri-axial accelerometer based fall-detection algorithms during scripted and continuous unscripted activities. *J Biomech*. 2010; 43(15):3051–3057. [PubMed: 20926081]
35. Bourke AK, Lyons GM. A threshold-based fall-detection algorithm using a bi-axial gyroscope sensor. *Med Eng Phys*. 2008; 30(1):84–90. [PubMed: 17222579]

36. Bourke AK, O'Donovan KJ, O'Laighin GM. Distinguishing falls from normal ADL using vertical velocity profiles. *Conf Proc IEEE Eng Med Biol Soc.* 2007;3176–3179. [PubMed: 18002670]
37. Bourke AK, O'Donovan KJ, Nelson J, O'Laighin GM. Fall-detection through vertical velocity thresholding using a tri-axial accelerometer characterized using an optical motion-capture system. *Conf Proc IEEE Eng Med Biol Soc.* 2008;2832–2835. [PubMed: 19163295]
38. Bourke AK, O'Donovan KJ, O'Laighin G. The identification of vertical velocity profiles using an inertial sensor to investigate pre-impact detection of falls. *Med Eng Phys.* 2008; 30(7):937–946. [PubMed: 18243034]
39. Lee Y, Lee M. Accelerometer sensor module and fall detection monitoring system based on wireless sensor network for e-health applications. *Telemed J E Health.* 2008; 14(6):587–592. [PubMed: 18729759]
40. Lee Y, Kim J, Son M, Lee M. Implementation of accelerometer sensor module and fall detection monitoring system based on wireless sensor network. *Conf Proc IEEE Eng Med Biol Soc.* 2007;2315–2318. [PubMed: 18002455]
41. Zigel Y, Litvak D, Gannot I. A method for automatic fall detection of elderly people using floor vibrations and sound--proof of concept on human mimicking doll falls. *IEEE Trans Biomed Eng.* 2009; 56(12):2858–2867. [PubMed: 19709955]
42. Litvak D, Zigel Y, Gannot I. Fall detection of elderly through floor vibrations and sound. *Conf Proc IEEE Eng Med Biol Soc.* 2008;4632–4635. [PubMed: 19163748]
43. Bourennane W, Charlon Y, Bettahar F, Campo E, Esteve D. Homecare monitoring system: A technical proposal for the safety of the elderly experimented in an Alzheimer's care unit. *IRBM.* 2013; 34(2):92–100.
44. Charlon Y, Bourennane W, Bettahar F, Campo E. Activity monitoring system for elderly in a context of smart home. *IRBM.* 2013; 34(1):60–63.
45. Quagliarella L, Sasanelli N, Belgiovine G. An interactive fall and loss of consciousness detector system. *Gait Posture.* 2008; 28(4):699–702. [PubMed: 18657976]
46. Quagliarella L, Sasanelli N, Belgiovine G. Performances of an accelerometric device for detecting fall and loss of consciousness. *J Appl Biomater Biomech.* 2008; 6(2):119–126. [PubMed: 20740455]
47. Lee T, Mihailidis A. An intelligent emergency response system: preliminary development and testing of automated fall detection. *J Telemed Telecare.* 2005; 11(4):194–198. [PubMed: 15969795]
48. Mihailidis, A.; Lee, T. [Accessed 6/27/2013] The role of technology in enhancing safety in the home: detection of fall and emergency situations. <http://www.healthplexus.net>
49. Nyan MN, Tay FE, Tan AW, Seah KH. Distinguishing fall activities from normal activities by angular rate characteristics and high-speed camera characterization. *Med Eng Phys.* 2006; 28(8): 842–849. [PubMed: 16406739]
50. Lee RY, Carlisle AJ. Detection of falls using accelerometers and mobile phone technology. *Age Ageing.* 2011; 40(6):690–696. [PubMed: 21596711]
51. Lindemann U, Hock A, Stuber M, Keck W, Becker C. Evaluation of a fall detector based on accelerometers: a pilot study. *Med Biol Eng Comput.* 2005; 43(5):548–551. [PubMed: 16411625]
52. Bloch F, Gautier V, Noury N, et al. Evaluation under real-life conditions of a stand-alone fall detector for the elderly subjects. *Ann Phys Rehabil Med.* 2011; 54(6):391–398. [PubMed: 21903502]
53. Albert MV, Kording K, Herrmann M, Jayaraman A. Fall classification by machine learning using mobile phones. *PLoS One.* 2012; 7(5):e36556. [PubMed: 22586477]
54. Aziz O, Robinovitch SN. An analysis of the accuracy of wearable sensors for classifying the causes of falls in humans. *IEEE Trans Neural Syst Rehabil Eng.* 2011; 19(6):670–676. [PubMed: 21859608]
55. Bianchi F, Redmond SJ, Narayanan MR, Cerutti S, Lovell NH. Barometric pressure and triaxial accelerometry-based falls event detection. *IEEE Trans Neural Syst Rehabil Eng.* 2010; 18(6):619–627. [PubMed: 20805056]

56. Bianchi F, Redmond SJ, Narayanan MR, Cerutti S, Celler BG, Lovell NH. Falls event detection using triaxial accelerometry and barometric pressure measurement. *Conf Proc IEEE Eng Med Biol Soc.* 2009;6111–6114. [PubMed: 19965262]
57. Boissy P, Choquette S, Hamel M, Noury N. User-based motion sensing and fuzzy logic for automated fall detection in older adults. *Telemed J E Health.* 2007; 13(6):683–693. [PubMed: 18092929]
58. Bourke AK, van de Ven PW, Chaya AE, O'Laughlin GM, Nelson J. The design and development of a long-term fall detection system incorporated into a custom vest for the elderly. *Conf Proc IEEE Eng Med Biol Soc.* 2008:2836–2839. [PubMed: 19163296]
59. Boyle J, Karunanithi M. Simulated fall detection via accelerometers. *Conf Proc IEEE Eng Med Biol Soc.* 2008:1274–1277. [PubMed: 19162899]
60. Campo E, Grangereau E. Wireless fall sensor with GPS location for monitoring the elderly. *Conf Proc IEEE Eng Med Biol Soc.* 2008:498–501. [PubMed: 19162702]
61. Chang SY, Lai CF, Chao HC, Park JH, Huang YM. An environmental-adaptive fall detection system on mobile device. *J Med Syst.* 2011; 35(5):1299–1312. [PubMed: 21424848]
62. Chao PK, Chan HL, Tang FT, Chen YC, Wong MK. A comparison of automatic fall detection by the cross-product and magnitude of tri-axial acceleration. *Physiol Meas.* 2009; 30(10):1027–1037. [PubMed: 19713595]
63. de la Guia Solaz M, Bourke A, Conway R, Nelson J, O'Laughlin G. Real-time low-energy fall detection algorithm with a programmable truncated MAC. *Conf Proc IEEE Eng Med Biol Soc.* 2010:2423–2426. [PubMed: 21095956]
64. Diaz, A.; Prado, M.; Roa, LM.; Reina-Tosina, J.; Sanchez, G. Preliminary evaluation of a full-time falling monitor for the elderly; San Francisco, USA. In: *Proceedings of the 26th Annual International Conference of the IEEE-EMBS*; Sept 1–5, 2004;
65. Dinh A, Teng D, Chen L, et al. Data acquisition system using six degree-of-freedom inertia sensor and ZigBee wireless link for fall detection and prevention. *Conf Proc IEEE Eng Med Biol Soc.* 2008:2353–2356. [PubMed: 19163174]
66. Estudillo-Valderrama MA, Roa LM, Reina-Tosina J, Naranjo-Hernández D. Design and implementation of a distributed fall detection system--personal server. *IEEE Trans Inf Technol Biomed.* 2009; 13(6):874–881. [PubMed: 19775977]
67. Godfrey A, Bourke AK, O'Laughlin GM, van de Ven P, Nelson J. Activity classification using a single chest mounted tri-axial accelerometer. *Med Eng Phys.* 2011; 33(9):1127–1135. [PubMed: 21636308]
68. Huang C-N, Chiang CY, Chen G, Hsu S, Chu W, Chan C. Fall detection system for healthcare quality improvement in residential care facilities. *J Med Biol Eng.* 2010; 30(4):247–252.
69. Hwang JY, Kang JM, Jang YW, Kim H. Development of novel algorithm and real-time monitoring ambulatory system using Bluetooth module for fall detection in the elderly. *Conf Proc IEEE Eng Med Biol Soc.* 2004; 3:2204–2207. [PubMed: 17272163]
70. Kang DW, Choi JS, Lee JW, Chung SC, Park SJ, Tack GR. Real-time elderly activity monitoring system based on a tri-axial accelerometer. *Disabil Rehabil Assist Technol.* 2010; 5(4):247–253. [PubMed: 20302417]
71. Kangas M, Konttila A, Winblad I, Jämsä T. Determination of simple thresholds for accelerometry-based parameters for fall detection. *Conf Proc IEEE Eng Med Biol Soc.* 2007:1367–1370. [PubMed: 18002218]
72. Kangas M, Konttila A, Lindgren P, Winblad I, Jämsä T. Comparison of low-complexity fall detection algorithms for body attached accelerometers. *Gait Posture.* 2008; 28(2):285–291. [PubMed: 18294851]
73. Karantonis DM, Narayanan MR, Mathie M, Lovell NH, Celler BG. Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. *IEEE Trans Inf Technol Biomed.* 2006; 10(1):156–167. [PubMed: 16445260]
74. Naranjo-Hernandez D, Roa LM, Reina-Tosina J, Estudillo-Valderrama MA. Personalization and adaptation to the medium and context in a fall detection system. *IEEE Trans Inf Technol Biomed.* 2012; 16(2):264–271. [PubMed: 22287249]

75. Nguyen TT, Cho MC, Lee TS. Automatic fall detection using wearable biomedical signal measurement terminal. *Conf Proc IEEE Eng Med Biol Soc.* 2009:5203–5206. [PubMed: 19964661]
76. Niazmand K, Jehle C, D'Angelo LT, Lueth TC. A new washable low-cost garment for everyday fall detection. *Conf Proc IEEE Eng Med Biol Soc.* 2010:6377–6380. [PubMed: 21096697]
77. Nocua R, Noury N, Gehin C, Dittmar A, McAdams E. Evaluation of the autonomic nervous system for fall detection. *Conf Proc IEEE Eng Med Biol Soc.* 2009:3225–3228. [PubMed: 19964061]
78. Noury, N.; Barralon, P.; Virone, G.; Boissy, P.; Hamel, M.; Rumeau, P. A smart sensor based on rules and its evaluation in daily routines; Cancun, Mexico. In: *Proceedings of the 25th Annual International Conference of the IEEE-EMBS*; Sept 17–21, 2003;
79. Nyan MN, Tay FE, Murugasu E. A wearable system for pre-impact fall detection. *J Biomech.* 2008; 41(16):3475–3481. [PubMed: 18996529]
80. Sim SY, Jeon HS, Chung GS, et al. Fall detection algorithm for the elderly using acceleration sensors on the shoes. *Conf Proc IEEE Eng Med Biol Soc.* 2011:4935–4938. [PubMed: 22255445]
81. Tamura T, Yoshimura T, Sekine M, Uchida M, Tanaka O. A wearable airbag to prevent fall injuries. *IEEE Trans Inf Technol Biomed.* 2009; 13(6):910–914. [PubMed: 19846379]
82. Tolkiehn M, Atallah L, Lo B, Yang GZ. Direction sensitive fall detection using a triaxial accelerometer and a barometric pressure sensor. *Conf Proc IEEE Eng Med Biol Soc.* 2011:369–372. [PubMed: 22254325]
83. Wu G, Xue S. Portable preimpact fall detector with inertial sensors. *IEEE Trans Neural Syst Rehabil Eng.* 2008; 16(2):178–183. [PubMed: 18403286]
84. Yuwono M, Moulton BD, Su SW, Celler BG, Nguyen HT. Unsupervised machine-learning method for improving the performance of ambulatory fall-detection systems. *Biomed Eng Online.* 2012; 11:9. [PubMed: 22336100]
85. Zhang T, Wang J, Liu P, Hou J. Fall detection by embedding an accelerometer in cellphone and using KFD algorithm. *IJCSNS.* 2006; 6(10):277–284.
86. Auvinet E, Multon F, Saint-Arnaud A, Rousseau J, Meunier J. Fall detection with multiple cameras: an occlusion-resistant method based on 3-D silhouette vertical distribution. *IEEE Trans Inf Technol Biomed.* 2011; 15(2):290–300. [PubMed: 20952341]
87. Auvinet E, Reveret L, St-Arnaud A, Rousseau J, Meunier J. Fall detection using multiple cameras. *Conf Proc IEEE Eng Med Biol Soc.* 2008:2554–2557. [PubMed: 19163224]
88. Nyan MN, Tay FE, Mah MZ. Application of motion analysis system in pre-impact fall detection. *J Biomech.* 2008; 41(10):2297–2304. [PubMed: 18589428]
89. Li Y, Ho KC, Popescu M. A microphone array system for automatic fall detection. *IEEE Trans Biomed Eng.* 2012; 59(5):1291–1301. [PubMed: 22532430]
90. Popescu, M.; Mahnot, A. Acoustic fall detection using one-class classifiers; Minneapolis, Minnesota, USA. In: *Proceedings of the 31st Annual International Conference of the IEEE-EMBS*; Sept 3–6 2009;
91. Rimminen H, Lindström J, Linnavuo M, Sepponen R. Detection of falls among the elderly by a floor sensor using the electric near field. *IEEE Trans Inf Technol Biomed.* 2010; 14(6):1475–1476. [PubMed: 20525533]
92. Chia-Wen, L.; Zhi-Hong, L. Automatic Fall Incident Detection in Compressed Video for Intelligent Homecare; Honolulu, Hawaii, USA. In: *Proceedings of the 16th International Conference on Computer on Communications and Networks*; Aug 13–16, 2007;
93. Foroughi, H.; Aski, BS.; Pourreza, H. Intelligent video surveillance for monitoring fall detection of elderly in home environments; Khulna, Bangladesh. In: *Proceedings of the 11th International Conference on Computer and Information Technology*; Dec 25–27 2008;
94. Lee YS, Chung WY. Visual sensor based abnormal event detection with moving shadow removal in home healthcare applications. *Sensors (Basel).* 2012; 12(1):573–584. [PubMed: 22368486]
95. Leone A, Diraco G, Siciliano P. Detecting falls with 3D range camera in ambient assisted living applications: a preliminary study. *Med Eng Phys.* 2011; 33(6):770–781. [PubMed: 21382737]
96. Mirmahboub B, Samavi S, Karimi N, Shirani S. Automatic monocular system for human fall detection based on variations in silhouette area. *IEEE Trans Biomed Eng.* 2013; 60(2):427–436. [PubMed: 23192468]

97. Rougier, C.; Meunier, J.; St-Arnaud, A.; Rousseau, J. Monocular 3D Head Tracking to Detect Falls of Elderly People; New York City, New York, USA. In: Proceedings of the 28th Annual International Conference of the IEEE-EMBS; Aug 30-Sept 3, 2006;
98. Rougier, C.; Meunier, J.; St-Arnaud, A.; Rousseau, J. Fall Detection from Human Shape and Motion History Using Video Surveillance; Niagara Falls, Canada. In: 21st International Conference on Advanced Information Networking and Applications Workshop; May 21–23 2007;
99. Shieh WY, Huang JC. Falling-incident detection and throughput enhancement in a multi-camera video-surveillance system. *Med Eng Phys.* 2012; 34(7):954–963. [PubMed: 22154761]
100. Gietzelt M, Spehr J, Ehmen Y, et al. GAL@Home: a feasibility study of sensor-based in-home fall detection. *Z Gerontol Geriatr.* 2012 Dec; 45(8):716–721. [PubMed: 23184297]
101. Ariani A, Redmond SJ, Chang D, Lovell NH. Software simulation of unobtrusive falls detection at night-time using passive infrared and pressure mat sensors. *Conf Proc IEEE Eng Med Biol Soc.* 2010:2115–2118. [PubMed: 21096573]
102. Ariani A, Redmond SJ, Chang D, Lovell NH. Simulated Unobtrusive Falls Detection With Multiple Persons. *IEEE Trans Biomed Eng.* 2012; 59(11):3185–3196. [PubMed: 22835529]
103. Doukas CN, Maglogiannis I. Emergency fall incidents detection in assisted living environments utilizing motion, sound, and visual perceptual components. *IEEE Trans Inf Technol Biomed.* 2011; 15(2):277–289. [PubMed: 21062686]
104. Srinivasan S, Han J, Lal D, Gacic A. Towards automatic detection of falls using wireless sensors. *Conf Proc IEEE Eng Med Biol Soc.* 2007:1379–1382. [PubMed: 18002221]
105. Tasoulis SK, Doukas CN, Maglogiannis I, Plagianakos VP. Statistical data mining of streaming motion data for fall detection in assistive environments. *Conf Proc IEEE Eng Med Biol Soc.* 2011:3720–3723. [PubMed: 22255148]
106. Zhang Z, Kapoor U, Narayanan M, Lovell NH, Redmond SJ. Design of an unobtrusive wireless sensor network for nighttime falls detection. *Conf Proc IEEE Eng Med Biol Soc.* 2011:5275–5278. [PubMed: 22255528]
107. Prado-Velasco M, del Rio-Cidoncha MG, Ortiz-Marin R. The inescapable smart impact detection system (ISIS): An ubiquitous and personalized fall detector based on a distributed ‘divide and conquer strategy’. *Conf Proc IEEE Eng Med Biol Soc.* 2008:3332–3335. [PubMed: 19163421]
108. Doughty K, Lewis R, McIntosh A. The design of a practical and reliable fall detector for community and institutional telecare. *J Telemed Telecare.* 2000; 6(suppl 1):S150–S154. [PubMed: 10794003]
109. Otto CA, Chen X. Automated fall detection: saving senior lives one fall at a time. *Caring.* 2009; 28(3):44–46. [PubMed: 19402442]
110. Narayanan MR, Lord SR, Budge MM, Celler BG, Lovell NH. Falls management: detection and prevention, using a waist-mounted triaxial accelerometer. *Conf Proc IEEE Eng Med Biol Soc.* 2007:4037–4040. [PubMed: 18002885]
111. Depursinge Y, Krauss J, El-khoury Ms. inventors; Device for monitoring the activity of a person and/or detecting a fall, in particular with a view to providing help in the event of an incident hazardous to life or limb. United States Patent US6201476 B1. Mar 13.:2001.
112. Prado, M.; Reina-Tosina, J.; Roa, L. Distributed intelligent architecture for falling detection and physical activity analysis in the elderly; Houston, Texas, USA. Houston, Texas, USA. In: Proceedings of the 24th Annual International Conference of the IEEE-EMBS; Oct 23–26. 2002;
113. Bourke AK, O’Donovan K, Clifford A, ÓLaighin G, Nelson J. Optimum gravity vector and vertical acceleration estimation using a tri-axial accelerometer for falls and normal activities. *Conf Proc IEEE Eng Med Biol Soc.* 2011:7896–7899. [PubMed: 22256171]
114. Mathie, MJ.; Basilakis, J.; Celler, BG. A system for monitoring posture and physical activity using accelerometers; Istanbul, Turkey. In: Proceedings of the 23th Annual International Conference of the IEEE-EMBS; Oct 23–26, 2001;
115. Tamura, T.; Yoshimura, T.; Horiuchi, F.; Higashi, Y.; Fujimoto, T. An ambulatory fall monitor for the elderly; Chicago, Illinois, USA. In: Proceedings of the 22nd International Conference on Engineering in Medicine and Biology Society; Jul 23–28, 2000;

116. Van Wieringen M, Eklund J. Real-time signal processing of accelerometer data for wearable medical patient monitoring devices. *Conf Proc IEEE Eng Med Biol Soc.* 2008:2397–2400. [PubMed: 19163185]
117. Tamura T, Yoshimura T, Sekine M. A preliminary study to demonstrate the use of an air bag device to prevent fall-related injuries. *Conf Proc IEEE Eng Med Biol Soc.* 2007:3833–3835. [PubMed: 18002834]
118. Fernandez-Luque FJ, Zapata J, Ruiz R. A system for ubiquitous fall monitoring at home via a wireless sensor network. *Conf Proc IEEE Eng Med Biol Soc.* 2010:2246–2249. [PubMed: 21096580]
119. Noury, N.; Herve, T.; Rialle, V., et al. Monitoring behavior in home using a smart fall sensor and position sensors; Lyon, France. In: 1st International Conference on Microtechnologies in Medicine and Biology; Oct 12–14 2000;
120. Villacorta JJ, Jiménez MI, Del Val L, Izquierdo A. A configurable sensor network applied to ambient assisted living. *Sensors (Basel).* 2011; 11(11):10724–10737. [PubMed: 22346668]
121. Wu G. Distinguishing fall activities from normal activities by velocity characteristics. *J Biomech.* 2000; 33(11):1497–1500. [PubMed: 10940409]
122. Nait-Charif, H.; McKenna, SJ. Activity summarisation and fall detection in a supportive home environment; Cambridge, England, UK. In: 17th International Conference on Pattern Recognition; Aug 23–26 2004;
123. Anderson, D.; Keller, JM.; Skubic, M.; Xi, C.; Zhihai, H. Recognizing Falls from Silhouettes; New York City, New York, USA. In: Proceedings of the 28th Annual International Conference of the IEEE-EMBS; Aug 30-Sept 3 2006;
124. Spher, J.; Gvercin, M.; Winkelbach, S.; Steinhagen-Thiessne, E.; Wahl, F. Visual fall detection in home environments; Pisa, Italy. In: 6th International Conference of the International Society of Gerontechnology; Jun 4–5, 2008;
125. Della Toffola L, Patel S, Chen BR, Ozsecen YM, Puiatti A, Bonato P. Development of a platform to combine sensor networks and home robots to improve fall detection in the home environment. *Conf Proc IEEE Eng Med Biol Soc.* 2011:5331–5334. [PubMed: 22255542]
126. Cucchiara R, Prati A, Vezzanie R. A multi-camera vision system for fall detection and alarm generation. *Expert Systems.* 2007; 24(5):334–345.
127. Sposaro F, Tyson G. iFall: an Android application for fall monitoring and response. *Conf Proc IEEE Eng Med Biol Soc.* 2009:6119–6122. [PubMed: 19965264]
128. Mellone S, Tacconi C, Schwickert L, Klenk J, Becker C, Chiari L. Smartphone-based solutions for fall detection and prevention: the FARSEEING approach. *Z Gerontol Geriatr.* 2012; 45(8): 722–727. [PubMed: 23184298]
129. Kangas M, Vikman I, Nyberg L, Korpelainen R, Lindblom J, Jämsä T. Comparison of real-life accidental falls in older people with experimental falls in middle-aged test subjects. *Gait Posture.* 2012; 35(3):500–505. [PubMed: 22169389]
130. Patel PA, Gunnarsson C. A Passive Monitoring System in Assisted Living Facilities: 12-Month Comparative Study. *Phys Occup Ther Geriatr.* 2012; 30(1):45–52. [PubMed: 22448082]
131. Gövercin M, Költzsch Y, Meis M, et al. Defining the user requirements for wearable and optical fall prediction and fall detection devices for home use. *Inform Health Soc Care.* 2010; 35(3–4): 177–187. [PubMed: 21133771]
132. Noury N, Galay A, Pasquier J, Ballussaud M. Preliminary investigation into the use of Autonomous Fall Detectors. *Conf Proc IEEE Eng Med Biol Soc.* 2008:2828–2831. [PubMed: 19163294]
133. Aud MA, Abbott CC, Tyrer HW, et al. Smart Carpet: Developing a sensor system to detect falls and summon assistance. *J Gerontol Nurs.* 2010; 36(7):8–12. [PubMed: 20608585]
134. Horton K. Falls in older people: the place of telemonitoring in rehabilitation. *J Rehabil Res Dev.* 2008; 45(8):1183–1194. [PubMed: 19235119]
135. Londei ST, Rousseau J, Ducharme F, et al. An intelligent videomonitoring system for fall detection at home: perceptions of elderly people. *J Telemed Telecare.* 2009; 15(8):383–390. [PubMed: 19948704]

136. Marquis-Faulkes F, McKenna SJ, Newell AF, Gregor P. Gathering the requirements for a fall monitor using drama and video with older people. *Technol Disabil.* 2005; 17(4):227–236.
137. Brownsell S, Hawley M. Fall detectors: do they work or reduce the fear of falling? *Housing, Care and Support.* 2004; 7(1):18–24.
138. Brownsell SJ, Bradley DA, Bragg R, Catlin P, Carlier J. Do community alarm users want telecare? *J Telemed Telecare.* 2000; 6(4):199–204. [PubMed: 11027119]
139. Klenk J, Becker C, Lieken F, et al. Comparison of acceleration signals of simulated and real-world backward falls. *Med Eng Phys.* 2011; 33(3):368–373. [PubMed: 21123104]
140. Bagalà F, Becker C, Cappello A, et al. Evaluation of accelerometer-based fall detection algorithms on real-world falls. *PLoS One.* 2012; 7(5):e37062. [PubMed: 22615890]
141. Wilding MJ, Seegert L, Rucic S, Griffin M, Kachnowski S, Parasuraman S. Falling short: Recruiting elderly individuals for a fall study. *Ageing Res Rev.* 2013; 12(2):552–560. [PubMed: 23274452]

Appendix A

Example Search Strategy for PubMed

1. "Monitoring, Ambulatory"[Mesh] AND "Accidental Falls"[Mesh]
Or
2. "Accidental Falls"[majr] AND ("Monitoring, Ambulatory"[Mesh] OR "instrumentation" [Subheading] OR "Clinical Alarms"[Mesh])
Or
3. ("Accidental Falls"[majr]) AND ("Monitoring, Physiologic"[Mesh] OR "instrumentation" [Subheading] OR "Clinical Alarms"[Mesh])
AND
English [Language]

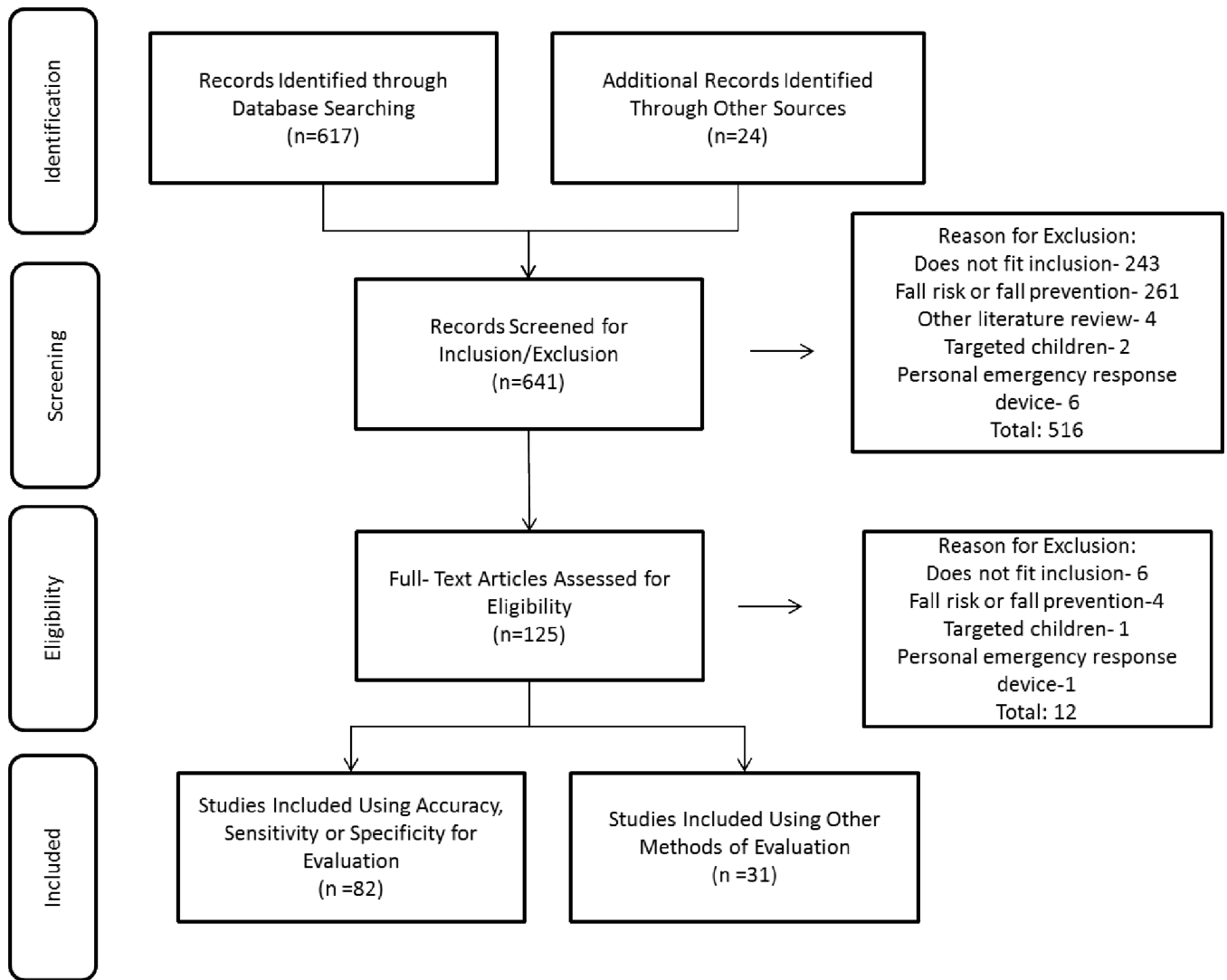


Figure 1.
Flow Diagram of the literature review.