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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 results 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, rhabdomyolosis 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 detect falls. [24–26] Non-wearable systems include cameras, [27–29] acoustic sensors [30, 31] and pressure sensors [32] 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 homes[100] 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 results 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.

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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]

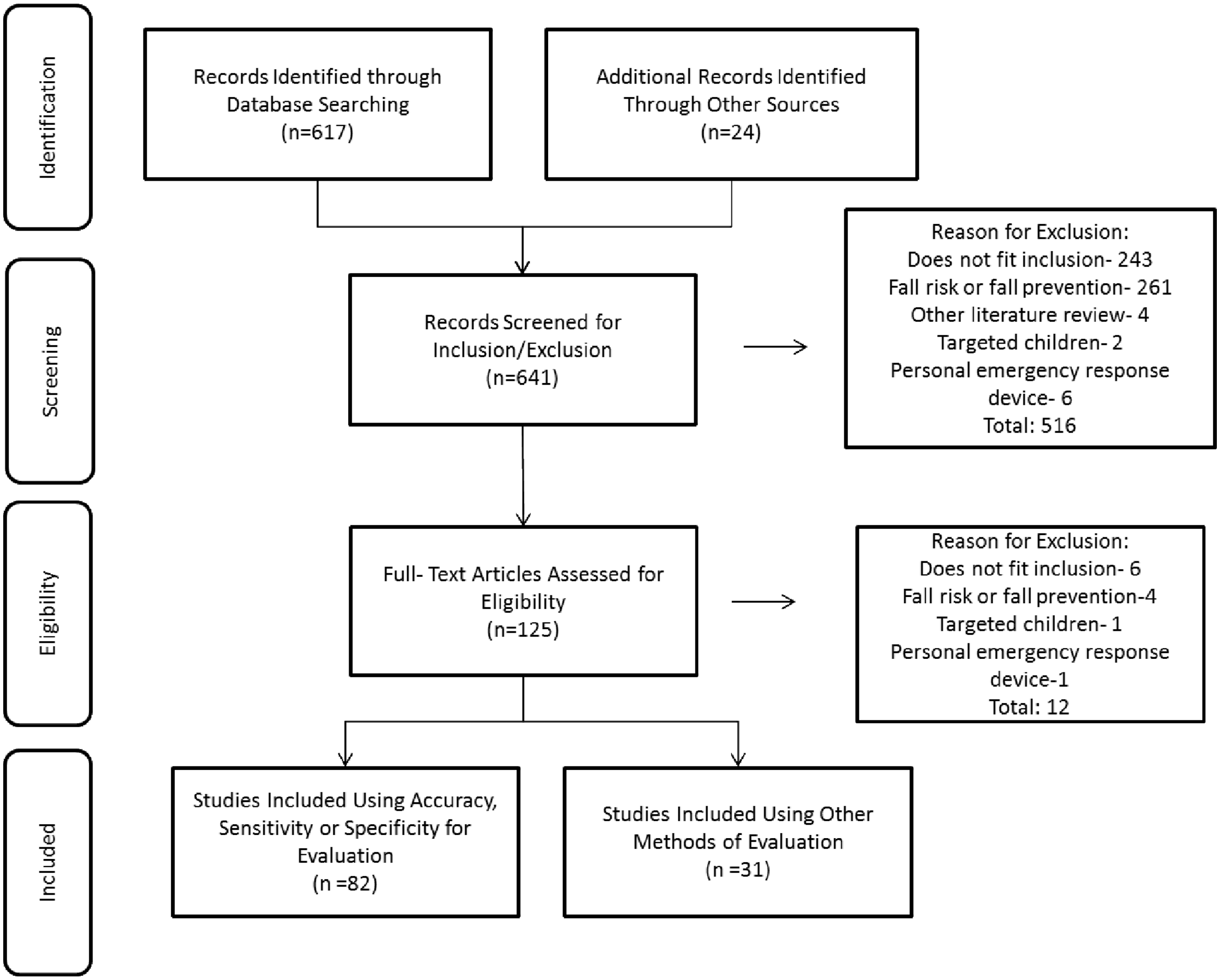

Figure 1.

Flow Diagram of the literature review.